A Gaussian Process-Based Ground Segmentation for Sloped Terrains

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Abstract—A Gaussian Process (GP) based ground segmentation method is proposed in this paper which is fully developed in a probabilistic framework. The proposed method tends to obtain a continuous realistic model of the ground. The LiDAR three-dimensional point cloud data is used as the sole source of the input data. The physical realities of the data are taken into account to properly classify sloped ground as well as the flat ones. Furthermore, unlike conventional ground segmentation methods, no height or distance constraints or limitations are required for the algorithm to be applied to take all the regarding physical behavior of the ground into account. Furthermore, a density-like parameter is defined to handle ground-like obstacle points in the ground candidate set. The non-stationary covariance kernel function is used for the Gaussian Process, by which Bayesian inference is applied using the maximum A Posteriori criterion. The log-marginal likelihood function is assumed to be a multi-task objective function, to represent a whole-frame unbiased view of the ground at each frame. Simulation results show the effectiveness of the proposed method even in an uneven, rough scene which outperforms similar Gaussian process-based ground segmentation methods.

Index Terms—Gaussian Process Regression, Ground Segmentation, Non-stationary Covariance Function, non-smooth data, Gradient Roads.

I. INTRODUCTION

The imminent advent of level five autonomy of driver–less cars is not favorable anymore to be considered as one’s far-fetched ambition. Autonomous Land Vehicle’s (ALV) may provide many opportunities to empowering the ability of remote exploration and navigation in an unknown environment to establishing driver–less cars that may navigate autonomously in urban areas while being safer by compensating human driving faults. Therefore, ALVs are expected to conquer the urban transportation industry soon enough if they meet certain performance prerequisites. Safe maneuvers in urban areas through different obstacles and during different possible scenarios would be considered as one of such highly consequential prerequisites. To establish such a driver–less car, developed methods shall be reliable and real-time implementable. This reliability is obtained only if ALVs are capable of obtaining a detailed and reliable perception of the environment they are tending to perform in. Detailed perception of the urban environment in which driver-less cars are operating is often obtained by pre-and post-processing of raw data frames coming from its sensors. Different objects and obstacles in each scene must be detected and classified to construct the needed perception. While different detection and classification methods are proposed to tackle this problem, ground segmentation remains a vital part of this classification procedure as the vehicle will plan its future possible routes and reactions on a possible space that is defined based on the ground. Thus, ALVs shall efficiently recognize the ground in unknown environments they tend to operate. Although a reliable ground segmentation procedure shall be applicable in environments with both flat and sloped terrains the issue remains not fully solved in the literature.

Gaussian process regressions are useful tools for the implementation of Bayesian inference which relies on correlation models of inputs and observation data [1]. Although light detection and ranging (LiDAR) sensors are commonly used in ALVs, data resulting from these sensors do not inherit smoothness, and therefore, stationary covariance functions may not be used to implement Gaussian regression tasks on these data. Different methods for segmentation have been proposed in the literature with these constraints [2]–[8].

In [2], the ground surface is obtained in an iterative routine, using deterministic assignment of the seed points. In [3], the ground segmentation step is put aside to establish a faster segmentation based on Gaussian process regression. Thus, A 2D occupancy grid is used to determine surrounding ground heights, and a set of non-ground candidate points are generated. Reference [4] handles real-time segmentation problem by differentiating the minimum and maximum height map in both rectangular and a polar grid map. In [5] a geometric ground estimation is obtained by a piece-wise plane fitting method capable of estimating arbitrary ground surfaces.

In [6] a Gaussian process-based methodology is used to perform ground estimation by segmenting the data with a fast segmentation method firstly introduced by [7]. The non-stationary covariance function from [9] is used to model the ground observations while no specific physical motivated method is given for choosing length scales. Paper [10] proposed a human-centric ground segmentation method based on processing the point cloud in both vertical and horizontal directions. Paper [8] proposes a fast segmentation method based on local convexity criterion in non-flat urban environments. The jump-convolution process is utilized in [11] to obtain a fast estimation of ground surface using LiDAR data without
any consideration of sloped ground segments.

These methods are either estimating ground piece-wise and with the local viewpoint or by labeling all the individual points with some predefined criterion. Except [6] none of the above-mentioned methods, gives a continuous model for the predicted ground. Furthermore, none of them gives an exact method to extract local characteristics of non-smooth data. However, efficient ground segmentation has to be done considering the physical properties of the data including non-smoothness of the LiDAR data and ground condition in every data frame. Thus, even direct assignment of slope values to length scales in [6] does not lead to the proper classification of ground points coming from sloped areas. This is because the careful specification of covariance structures is critical especially in non-parametric regression tasks [12].

LiDAR data consists of three-dimensional range data which is collected by a rotating sensor, strapped down to a moving car. This moving sensor causes non-smoothness in its measured data, which may not be taken into account using common stationary covariance functions. Although in some methods such as [6] a Gaussian process-based method for ground segmentation with non-stationary covariance functions are proposed, adjusting covariance kernels to accommodate the physical property of the ground segmentation problem needs further investigation.

Length-scales may be defined as the extent of the area that data points may affect on each other [13]. Length-scale values play a significant role in the quality of the interpretation that the covariance kernel gives about the data. A constant length scale may not be used with LiDAR data due to the non-smoothness of the collected point cloud. Different methods are proposed to adjust length scales locally for non-stationary covariance functions by assuming an exact functional relationship for length-scale values [14]–[16]. The ground segmentation method proposed by [6] assumes the length scales to be a defined function of line features in different segments. This is not sufficient because no physical background is considered for the selection of functional relationships and this function might change and fail to describe the underlying data in different locations.

The quality of the ground is not elaborated in each segment with disregard for adjacent segments. Furthermore, The physical properties of the data are taken into account for the method to be able to properly classify sloped ground as well as the flat ground. An intuitive guess of length-scale values are represented by assuming the existence of hypothetical surfaces in the environment that every bunch of data points has resulted from measurements of these surfaces. Thus, unlike other ground segmentation methods in the literature, no height or distance constraints or limitations are applied to the data which enables the data to take all the available information into account. This enables the method to gain a more clear and realistic view of the ground as it insists on the fact that the ground might not always be a flat segment or restricted from having heights more than certain values.

The proposed method tends to obviate the difficulties of ground segmentation in sloped areas by considering the two-dimensional line fitting method as the core of the line extraction algorithm in which the exact distance of the points to the line is taken into account instead of vertical distance which is the prevailing method in this field. Furthermore, a physically motivated line extraction algorithm is introduced which is intuitively compatible with what happens in real-world urban scenarios.

For the ground points placed adjacent to or beneath the obstacle points in 2D segments, a density-like parameter is introduced as a parameter in the GP kernel to make the ground estimation more reliable for these areas. This parameter gives a higher density-like value to the points related to line-segments with an obstacle in their proximity.

The three-dimensional LiDAR data is segmented using a radial grid map. Each LiDAR scan is divided into $m$ segments. Then each segment is divided into $n$ bins. Then, points with the lowest height in each bin are considered to be the ground candidate points in each segment. The proposed method is tested on KITTI [17] data set and the data set provided by [18] which is labeled. The method is shown to outperform similar Gaussian process-based ground segmentation methods and at the same time gives a proper estimation of sloped ground. All modules and algorithms are implemented and developed from scratch using C++ using Qt Creator. Furthermore, 3D point clouds are handled by the use of Point Cloud Library (PCL). A Gaussian Process Regression (GP) library is also developed in C++ based on the math provided in [1].

**II. RADIAL GRID MAP**

In order to arrange all the points at each segment according to their radial distance to the origin of $xy$-plane, each segment is divided into different bins with respect to its radial range [7]. Each particular segment will be divided unevenly into $N$ bins because the minimum and maximum of radial distances are different between individual segments and $n_{th}$ bin in $m_{th}$ segment $b_{nm}^n$ covers the range from $r_{min}$ to $r_{max}$. The set $P_{nm}^m$ is constructed which contains all of the three-dimensional points that are mapped into the $n_{th}$ bin of the $m_{th}$ segment [6], [7]. Furthermore the set $P_{nm}^m$ containing the corresponding two-dimensional points is constructed by,

$$P_{nm}^m = \{p_i = (r, z_i)^T \mid p_i \in P_{nm}^m\},$$

(1)
where, \( r_i = \sqrt{x_i^2 + y_i^2} \) is the radial range of corresponding points. The ground candidate set \( PG_m \), being the first intuitive guess for obtaining initial ground model is constructed by collecting the point with the lowest height at each bin as the ground candidate in that bin [6]:

\[
PG_m = \{ p_i' | p_i' \in P_n^m, z_i = \min(Z^m_n) \},
\]

where, \( Z^m_n \) denotes the set of height values of all points in the corresponding bin and segment. Furthermore, in each bin a vertical segmentation is applied. Each bin is divided into \( j \) vertical segments spread from minimum height \( z_{min} \) to \( z_{max} \). Then the number of points in each of these vertical segments are calculated and averaged on the range to obtain \( \tilde{p}^m_n \).

\[
\tilde{p}^m_n = \frac{1}{j} \sum_{i=1}^{j} (p_i)
\]

Where \( p_i \) is obtained by dividing the number of points in each vertical segment by the area of that segment.

### III. GAUSSIAN PROCESS REGRESSION

Gaussian processes (\( GP \)) are stochastic processes with any finite number of their random variables being jointly Gaussian distributed. In this paper, Gaussian process regression is being used as a tractable tool to put prior distributions over a nonlinear function that relates the ground model to the radial location of points. Gaussian processes are thoroughly defined by their mean and covariance function:

\[
f(x) \sim GP(m(x), k(x, x'))
\]

The predictive distribution of Gaussian process nonlinear regression is obtained from the joint distribution of the measurement and the function values [1], in which,

\[
\tilde{f}_s = K_X (K + \sigma^2_n I)^{-1} y,
\]

\[
cov = K_s - K_X (K + \sigma^2_n I)^{-1} K^T_X.
\]

Log marginal likelihood or evidence \( P(y|X) \) is obtained under Gaussian process assumption that the prior is Gaussian \( f|X \sim N(0, K) \):

\[
\log P(f|X) = -\frac{1}{2} f^T K^{-1} f - \frac{1}{2} \log |K| - \frac{n}{2} \log(2\pi).
\]

### IV. PHYSICALLY MOTIVATED GROUND SEGMENTATION

Different kinds of terrains might be wended by an ALV, in different kinds of environments and applications. Thus, flat and gradient roads and grounds might be faced by an ALV in urban scenarios. In this paper, a Gaussian process regression-based method is developed to consider both flat and sloped terrains in urban road driving scenes. This method estimates ground for separated segments with a multi-task objective function to take the whole-frame condition of ground into account.

In Gaussian process regression methods covariance kernels define how the parameters are related to each other and how they are being affected by each other due to their specific mathematical model at different extents. Although simple covariance kernels are powerful tools for Bayesian inference, they fail to consider local-smoothness, since in their simplest version they assume the data to be stationary. On the other hand, LiDAR data inherits “input-dependent smoothness”, meaning that its data does not bear smooth variation at every part and direction of the environment, thus the stationarity assumption fails to describe this data precisely. Therefore, covariance functions with constant length-scales are not suitable for LiDAR point cloud since for example flat grounds must have a length-scale that is more widely valid than a rough ground or the points coming from different parts of the data may not be assumed to behave regarding the same covariance kernel. The non-stationary covariance function originally represented by [9] is used to model ground in this paper.

\[
K(r_i, r_j) = \sigma^2_f \left[ L^2_1 \right]^{\frac{1}{4}} \left[ L^2_2 \right]^{\frac{1}{4}} \left[ \frac{L^2_1 + L^2_2}{2} \right]^{-\frac{1}{4}} \times \exp \left( -\frac{(r_i - r_j)^2}{2(L^2_1 + L^2_2)} \right).
\]

Local characteristics of this covariance function is calculated using local line features by assuming length-scales to be of the form \( L_i = a d_i \), where \( a \) is assumed to be one of the hyper-parameters of the regression problem.

\[
d_i = \frac{1}{\tilde{p}^m_n} \log \left( \frac{1}{y_i} \right)
\]

### A. Physically-Motivated Line Extraction

Different line extraction algorithms are being utilized in different robotics applications with some of them being more generally accepted and utilized. Although these algorithms are widely used, some applications need to use different versions of them [19], [6], [20]. Line extraction algorithms are previously used in different ground segmentation methods to enable the distinction of the ground and obstacle points. Thus, although these methods are effective in segmenting near-flat ground points, they fail to properly recognize ground points coming from sloped ground sections or gradient roads. [6] states that despite using a non-stationary covariance function as kernel, their method does not work in the existence of sloped terrains. This can be due to the usage of the Incremental line extraction algorithm which is elaborated in [21] and utilized in [6] to estimate ground surface. The incremental line extraction algorithm lacks the efficiency needed for the detection of sloped terrains. Thus a physically motivated line extraction algorithm along with a two-dimensional line method is introduced which is intuitively compatible with what happens in real-world urban scenarios. The proposed line extraction algorithm relies on the fact that in urban structures, the successive lines of each laser scan should be considered independently. For example, if some structures are found in the successive lines of each laser scan should be considered. The last point of this series is a "critical point", the parameters of the next line are calculated using local line features by assuming length-scales to be of the form \( L_i = a d_i \), where \( a \) is assumed to be one of the hyper-parameters of the regression problem.
sudden change of structure is more important than the overall behavior of some cluster of points as they may be related to a starting point of an obstacle or sloped ground.

a) Definition of Critical Points: To overcome the problem of sloped terrain detection in the ground segmentation task, the proposed line extraction algorithm operates based on finding some critical points among the ground candidate points set in each segment $PG_m$. The critical points are defined to be the points at which the behavior of the successive ground candidate points change in a way that can be flagged as unusual. This unusual behavior happens in the areas that the ground meets the obstacle or as well as the areas at which the road starts to elevate during a slope or gradient section of its. These critical points, therefore, partition each segment into different sections between each two successive critical points. The 2D points between two successive critical points form a line-segment. These line-segments should be chosen carefully as they play a significant role in the line extraction algorithm and the further interpretation of the ground. On the other hand, while large sloped line-segments relate to non-ground structures, the low sloped ones may relate to the road. Therefore, The conditions listed below must be met for a ground point to be considered as a critical point:

- **The slope of fitted line:** the slope of the fitted line for the potentially ground-related line segments must be greater than a threshold $\zeta_b$.
- **Distance from point to the fitted line:** distance from points of each line-segment to the fitted line must be less than a given threshold $\delta$.
- **Horizontal Distance of the points:** The horizontal distance of each two successive points must not exceed a given threshold $\zeta_m$. This is set to prevent including breakpoints. This threshold is set concerning each segment and about the radial size of each segment.
- **Smoothness of $\rho_m$:** The average number of vertical points must not have a sharp change during each line-segment.

b) Distance-oriented Line Regression: The distance-oriented line regression method is utilized as the core line fitting algorithm. The standard least square method breaks down when the slope of the line is almost vertical or when the slope of the line is large but finite [22]. The least-square method assumes that only the dependent variable is subject to error thus the distance of the points to the estimated value $(\hat{y} - y)^T(\hat{y} - y)$ is utilized. This assumption makes the algorithm very sensitive to the position of the independent value especially in larger slopes as depicted in Figure 2. In these cases, a small inaccuracy in the value of the regressor will lead to greater uncertainty in the value of the regressed parameter if the least square is used as the line fitting algorithm.

On the other hand, in many applications such as ground segmentation, this assumption fails to be true as both coordinates are subject to errors. Thus, the least square method is insufficient for sloped terrain ground point detection as the method tends to obtain critical points in areas with larger slopes and the accuracy of detection are of high importance here. The distance-oriented line regression method takes the exact distance of the points to the line into account. The orthogonal least square algorithm is utilized in [19] as an alternative for the least square method. The method assumes that both parameters have the same error while this assumption is not valid for line-segment extraction as the 2D value is derived by implementing manipulation on original 3D data. Furthermore, the Non-stationarity assumption of the method denies any similarity of errors in both directions. The mathematical model $y = \alpha + \beta \xi + \epsilon$ is assumed to describe the linear relationship of two underlying variables. If both of the variables are observed subject to a random error, the relation of these measurements are as follows:

$$r_i = \xi_i + \epsilon_{r_i},$$

$$z_i = \eta_i + \epsilon_{z_i} = \alpha + \beta \xi_i + \epsilon_{z_i}$$

In which $\epsilon_{r_i} \sim N(0, \sigma^2)$ and $\epsilon_{z_i} \sim N(0, \lambda \sigma^2)$. The maximum likelihood estimate for $\alpha$ and $\beta$ is derived. The "log-likelihood" has the following form:

$$L = -\frac{n}{2} \log(4\pi^2) - \frac{n}{2} \log(\lambda \sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^{n} (r_i - \xi_i)^2 - \frac{1}{2\lambda \sigma^2} \sum_{i=1}^{n} (z_i - \alpha - \beta \xi_i)^2$$

Differentiating the log-likelihood function with respect to $\alpha, \beta, \xi, \sigma$ and solving for $\frac{\partial L}{\partial \sigma}$ yields the numerical estimate of the line parameters.

B. Problem Formulation

Nonlinear Gaussian process regression problem is to recover a functional dependency of the form $y_i = f(x_i) + \epsilon_i$ from $n$ observed data points of the training set $D$. The set $PG_m\{(r_i, z_i)\}$ contains all of two-dimensional ground candidate points in the segment $m$ which the final ground model is inferred based on. The predictive ground model $P_m(z_i|r_i, R_m)$ for segment $m$ is built using the ground candidate set as the input for the Gaussian process regression task.

The covariance function $C$ is utilized as the $GP$'s kernel. The length-scale parameters $\mathcal{L}$ is set considering the evaluated
line-segments. This enables the predicted continuous ground model to show a reasonable distance to the minimum points set in non-ground sections. The predictive distribution of the height $z_*$ at the arbitrary test input location $r_*$ is obtained using the predictive ground model. Then the predicted ground values are compared to test input from the raw data to label ground points.

C. Problem Formulation

a) Physically–Motivated Length–Scales: Length-scales for each point in the ground candidate set as well as in the raw data are obtained as follows:

$$L_i = \begin{cases} \frac{\alpha}{p^*} \log \frac{1}{g} & \text{if } g_i \geq g_d \\ \alpha \log \frac{1}{g_d} & \text{O.W.} \end{cases}$$ (12)

The parameter $\alpha$ is the hyper-parameter for the regression task which will be learned based on the data. The $g_d$ threshold is set to prevent very large length-scale values when the slope is small and near zero. The term $\frac{1}{p^*}$ is related to the density of the points above each segment-line. This term adds an extra penalty-like value to the length scales. This makes sure that a reasonable distance will be kept with ground candidate points in high-density areas.

b) Ground Height Estimation: Predictive distribution of ground height can be addressed after obtaining length-scales on locations of ground candidate points. Predictive distribution $P_m(z_*)|r_*, R_m)$ enables the prediction of $z^*$ value at arbitrary locations $r^*$ at each point cloud frame:

$$\mu_{GP} = \tilde{z} = K(r^*, r)^T [K(r, r) + \sigma_n^2 I]^{-1} z,$$ (13)

in which, $K$ is the covariance matrix for $GP_z$ and $\sigma_n^2$ is the measurement noise. where, $\mathcal{L} \in \mathbb{R}$ is length scale for every data point.

D. Learning Hyper–Parameters

The behavior of the proposed model and its ability to adjust itself to the physical realities of the environment is directly affected by the values of hyper–parameters. Often in real-world applications, there is no exact prior knowledge about hyper–parameters’ values and they must be obtained from data.

Fig. 3: Implementation result of the ground segmentation method on three different segments of data with sloped terrains. Green points are real ground points labeled in [18]. Red dots are the point estimation of ground height in input test locations $r_*$ while blue points are the results of the method proposed in this paper. In c) Bigger points are the critical points detected in that segments.

Hyper–parameters $\theta = \{\sigma_f, \alpha, \sigma_n\}$ are mutually independent variables to allow the gradient-based optimization to hold its credibility. The maximum a posteriori argument is used to find the hyper–parameters for ground segmentation. The hyper–parameters that maximize the evidence of observing $z$ given $r$ or $log P(z|r, \mathcal{L})$. Gradient-based optimization methods are used to find the corresponding solutions.

E. Whole–Frame Objective Function

If optimization process is to be effective enough, it shall take all the segments into account to form an objective function. This would be an example of multi-task regression problem. The objective function in multi-task problems is equal to the sum of all objective functions regarding to different tasks of the problem that share the same hyper–parameters. Therefore, we assume that all the segments share the same hyper–parameters and establish a global view to our frame data in order to have the results to be whole–frame inclusive.

$$J(\theta) = \sum_{m=1}^{M} \left( \log P(z^m|r^m, \theta) \right)$$ (14)

$$= -\frac{1}{2} \sum_{m=1}^{M} \left( (z^m)^T A_m^{-1} z^m \right) + \log \left( \prod_{m=1}^{M} |A_m| \right)$$

$$+ \log(2\pi \left( \sum_{m=1}^{M} (n_m) \right))$$

where $A_m := K_m(r, r) + \sigma_n^2 I$ is the corresponding covariance function of Gaussian processes in each segment. Therefore,
in every segment the ground candidate set with assigned covariance kernels form the segment-wise objective function. Sum of all segment-wised objective functions will form the whole-frame objective function. For the whole-frame objective function to hold its credibility, the hyper-parameters of the regression task must be shared among all segments.

**V. SIMULATION AND RESULTS**

The method is fully developed in C++. All modules and algorithms are implemented and developed from scratch using C++ in Qt Creator. Furthermore, 3D point clouds are handled by the use of Point Cloud Library (PCL). A Gaussian process regression (GP) library is also developed in C++ based on the math provided in [1]. The block diagram of the implementation of the proposed method is presented in Figure 1. Data set in [18] is utilized to evaluate the results. To present the efficiency of the method for sloped terrains even in low height ground sections, segments are chosen that have slopes with more than 10 degrees or 18% inclination. The low height ground estimation result is presented in Figure 3. It is depicted that the proposed method is giving better estimation results for the sloped terrains. The average success rate of the proposed method is 93.5% for sloped areas while the rate for flat areas are equal to 96.7. The reported value from other methods is depicted in Table I. The best optimized kernel parameters \( \theta = (\sigma_f, a, \sigma_n) \) is reported as well for each segment.

The lower height simulation results for the sloped sections of the data are presented as in many available methods in the literature the evaluation results are presented for the height below 0.3m. In Figure 3a and 3b the simulation results of our proposed method are presented along with the simulation results of the method presented in [6] for the ground points up to 0.5m of height. The result proves the effectiveness of the proposed method to detect ground points even in sloped terrains. In Figure 3c results of the method are shown for a piece of data that both includes flat and sloped ground. Detected critical points are also depicted in the figure. The slope for \(3_{rd}\) the line-segment is near zero while the slope for \(4_{th}\) and \(5_{th}\) line-segment is more than 18% (11 degrees). But the test points belonging to the \(5_{th}\) line-segment (Highlighted by the rectangle) are classified as ground points. This is because the point density above this line-segment is not high, therefore the line-segment must be of a sloped ground, not an obstacle. Furthermore, as depicted in Figure 4 the results show that the proposed algorithm is effective on the whole data without any data truncation or other pre-processings leading to data omission, the advantage of which is the detection of the ground points which have greater heights or distance from the car. For example, most of the ground segmentation methods in the literature neglect all the points higher than 30cm. A line with 30cm height is depicted in Figure 3c and Figure 4. The method may neglect more than half of the ground points just by neglecting the heights greater than 0.3m. Although it is depicted that the ground points higher than 30cm are well detected by the proposed method. On the other hand, the ground point might be found in the far distance from the car as depicted in Figure 4.

Furthermore, in the colored rectangle at the distance 10 to 20m in Figure 4, the ground data is juxtaposed to an object’s points while both having the same range of height and gradient values. The algorithm finds it hard to maintain a continuous estimation of the ground as it is alerted by the value of \(\hat{\rho}\) that an obstacle might be placed here. The reason is that in this line-segment the density-like parameter \(\hat{\rho}\) is signaling the GP that a high number of points are available at the top of the ground candidate points, Therefore the estimation tries to keep its results near to the real ground points at the beginning but suddenly keeps its distance to the obstacle points.

Table II compares the processing time of different ground segmentation methods. Each frame of the data set presented by [18] contains approximately 70,000 three-dimensional points. The Velodyne LiDAR sensor captures data at 10 fps. The reported average processing time of the proposed method is based on the implementation of an Intel Core i7-7700HQ CPU @ 2.80GHz. The proposed method is able to operate at 14 fps which is about 1.5 times faster than the capture rate of the LiDAR sensors, making it suitable for real-time applications.
TABLE I: Average processing time and Success Rate (SR) of different ground segmentation methods.

| Method                                             | Average Processing Time per Frame (ms) | Average SR(flat/sloped) |
|----------------------------------------------------|---------------------------------------|-------------------------|
| Fast Ground Segmentation Method based on Jump-Convolution Network [22] | 4.7                                  | 94.61/91.25             |
| Loopy Belief Propagation Based Ground Segmentation [23] | 1000                                  | 97.19/NR                |
| Voxel-based Ground Segmentation [25]               | 19.31                                 | NR                      |
| Enhanced Ground Segmentation in Human-centric Robots [26] | 6.9                                   | 94.71/91.70             |
| Fast segmentation of 3D point clouds for ground vehicles [7] | 100                                  | NR                      |
| GP-Based Real-Time Ground Segmentation for ALVs [6] | ≈ 200                                 | 97.67 / NR              |
| Proposed Method                                     | 72.91                                 | 96.793.5                |

VI. CONCLUSIONS
A Physically-motivated ground segmentation algorithm is proposed for sloped terrains. The 3D LiDAR data is categorized based on a radial grid map to construct a segmentwise representation of 2D points. A line-segment dividing strategy is implemented on the 2D points of each segment based on the detection of critical points. The parameters regarding the line in each segment are obtained by a two-dimensional line regression algorithm that assumes non-equal error in both directions of the coordinate system. On the other hand, distance-related line fitting is utilized for the algorithm to be more effective in larger slopes. Furthermore, a density-like parameter is introduced to handle situations in which ground candidate points are just the minimum height points of on-road obstacles. Then based on these parameters a nonstationary covariance function is constructed and is fed to Gaussian process regression to obtain ground estimation. The method is tested on the labeled data set provided by [18]. The effectiveness of the proposed method is verified by the results of the test which outperforms similar methods in the sloped area and in the overall determination of ground points even when no data truncation is performed.

REFERENCES

[1] C. W. C. E. Rasmussen, Gaussian Processes for Machine Learning. MIT Press, 2006.
[2] D. Zermas, I. Izzat, and N. Papanikolopoulos, “Fast Segmentation of 3D Point Clouds: A Paradigm on LiDAR Data for Autonomous Vehicle Applications,” IEEE Int. Conf. Robot. Autom., no. May, pp. 5067–5073, 2017.
[3] M.-O. Shin, G.-M. Oh, S.-W. Kim, and S.-W. Soo, “Real-Time and Accurate Segmentation of 3-D Point Clouds Based on Gaussian Process Regression,” IEEE Trans. Intell. Transp. Syst., pp. 1–15, 2017. [Online]. Available: http://ieeexplore.ieee.org/document/7895118/
[4] D. Korchev, S. Cheng, Y. Owechko, and K. Kim, “On Real-Time LiDAR Data Segmentation and Classification,” Worldcomp-Proceedings.Com, no. February, 2016. [Online]. Available: http://www-personal.umich.edu/~ijuizhu/jihu/covar/Stein-Summary.pdf
[5] C. Plagemann, K. Kersting, and W. Burgard, “Nonstationary Gaussian process regression using point estimates of local smoothness,” Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics), vol. 5212 LNAl no. PART 2, pp. 204–219, 2008.
[6] A. Asvadi, C. Premebida, P. Peixoto, and U. Nunes, “3D Lidar-based algorithm using laser data based on seeded region growing,” Int. J. Intell. Veh. Syst. Proc., vol. 76, no. 3–4, pp. 563–582, 2014.
[7] Himmelsbach, M, von Hundlehausen, F, and H. Wuensche, “Fast segmentation of 3D point clouds for ground vehicles,” IEEE Int. Intell. Veh. Symp., pp. 560–565, 2010.
[8] F. Moosmann, O. Pink, and C. Stiller, “Segmentation of 3D lidar data in non-flat urban environments using a local convexity criterion,” IEEE Intell. Veh. Symp. Proc., pp. 215–220, 2009.
[9] C. J. Paciorek and M. J. Schervish, “Nonstationary Covariance Functions for Gaussian Process Regression,” pp. 1–27, 2003.
[10] P. M. Chu, S. Cho, J. Park, S. Fong, and K. Cho, “Enhanced ground segmentation method for Lidar point clouds in human-centric autonomous robot systems,” Human-Centric Computing and Information Sciences, 2019.
[11] Z. Shen, H. Liang, L. Lin, Z. Wang, W. Huang, and J. Yu, “Fast Ground Segmentation for 3D LiDAR Point Cloud Based on Jump-Convolution Process,” Remore Sensing, 2021.
[12] G. A. Fuglstad, D. Lindgren, D. Simpson, and H. Rue, “Exploring a new class of non-stationary spatial Gaussian random fields with varying local anisotropy,” arXiv, vol. 25, no. 1, pp. 1–28, 2013. [Online]. Available: http://arxiv.org/abs/1304.6949
[13] M. Stein, “Nonstationary spatial covariance functions,” Unpubl. Tech. report. Available, vol. 60637, pp. 0–7, 2005. [Online]. Available: http://www-personal.umich.edu/~ijuizhu/jihu/covar/Stein-Summary.pdf
[14] H. Gao, X. Zhang, Y. Fang, and J. Yuan, “A line segment extraction algorithm using 2D laser rangefinder for indoor long-range scanning,” 3D Research, Special Issue from RSS09, 2010.
[15] A. Siadat, A. Karke, S. Klausmann, M. Dufaut, and R. Husson, “An Optimized Segmentation Method for a 2-D Laser Scanner Applied to MobileRobot Navigation,” Proc. 3rd IFAC Symp. Intell. Components Instruments for Control Appl., no. JULY 1999, pp. 153–158, 1997.
[16] Y. Zhang and G. Luo, “Recurrent prediction algorithm for nonstationary Gaussian Process,” J. Syst. Softw., vol. 127, pp. 295–301, 2017. [Online]. Available: http://dx.doi.org/10.1016/j.jss.2016.08.036
[17] W. Ikram, K. Cho, Y.-S. Jeong, K. Um, and S. Sim, “Segmentation method for 3D point cloud,” in Proc. 3rd IFAC Symp. Intell. Components Instruments for Control Appl., no. JULY 1999, pp. 153–158, 1997.
[18] P. M. Chu, S. Cho, S. Sim, K. H. Kwak, and K. Cho, “A fast ground segmentation for 3D point cloud,” J. Inf. Process. Syst., vol. 13, pp. 491–499, 2017.
[19] P. M. Chu, S. Cho, S. Sim, K. H. Kwak, and K. Cho, “A fast ground segmentation method for 3D point cloud,” in Int. J. Intell. Veh. Syst. Proc., vol. 76, no. 3–4, pp. 563–582, 2014.
[20] S. Cho, J. Kim, W. Ikram, K. Cho, Y.-S. Jeong, K. Um, and S. Sim, “Sloped terrain segmentation for autonomous drive using sparse 3D point cloud,” The Scientific World Journa, vol. 2014, p. 9, 2014.
[21] S. Cho, J. Cho, S. Cho, J. Park, and S. F. K. Cho, “Enhanced ground segmentation method for Lidar point clouds in human-centric autonomous robot systems,” Human-Centric Computing and Information Science, 2019.