Traversable terrain classification for outdoor autonomous robots using single 2D laser scans

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Abstract. Interpreting laser data to allow autonomous robot navigation on paved as well as dirt roads using a fixed angle 2D laser scanner is a daunting task. This paper introduces an algorithm for terrain classification that fuses seven distinctly different classifiers: raw height, roughness, step size, curvature, slope, width and invalid data. These are then used to extract road borders, traversable terrain and identify obstacles. Experimental results are shown and discussed. The results were obtained using a DTU developed mobile robot, and the autonomous tests were conducted in a national park environment.

1. Introduction

Autonomous navigation by mobile robots in unstructured or semi-structured outdoor environments presents a considerable challenge. Adequately solving this challenge would allow robotic applications within industries such as agriculture, mining and logging. To achieve the level of autonomy required for such operation, a robot must be able to perceive and interpret the environment in a meaningful way. Limitations in current sensing technology coupled with a dynamically changing unknown environment, and difficulties in modeling the interaction between robot and terrain all make this task difficult.

Typical applications will require the robot to stay within certain boundaries (e.g. road borders) and avoid collision with other objects including other robots, vehicles, and humans. It is thus imperative for successful and safe autonomous navigation that the robot is able to identify obstacles or boundaries, which should not be crossed or collided with. The sensors used for this task could include vision, ultrasound, radar and laser scanner, both as combined solutions and each sensor type used individually. Multi sensor solutions would be expected to provide superior results but computational efforts and requirements of fast real-time classification make it interesting to explore what would be achievable with a single sensor.

Current work in the area tends to focus on using 3D laser scanners, vision or a combination of 3D laser scanners and vision. In vision solutions [2] argues that this problem can be divided into two subproblems: Lane following and obstacle detection, and describes a stereo vision based solution for both. Edge detection in vision systems is one of the possibilities to identify road borders and had some success already in 1986 as described in [14], color segmentation is used in [4] for tracking of dirt roads, road types similar to the ones used in this paper. A method for road following using vision and neural network was developed by [7]. A combined stereo vision and 2D laser scanner solution for outdoor obstacle avoidance is presented in [11]. Using 3D laser scanner solutions have been proposed by [13] by transforming point clouds into linear features, surfaces, and scatter. These were classified using a Bayesian filter based on a manually classified training set. Identification of navigable terrain using a 3D laser scanner by
This paper proposes a terrain classification algorithm that discriminates between obstacles and traversable terrain in single scans of a fixed 2D laser scanner. This is notoriously harder than using 3D sensor inputs as there is much less information available, but the cost, power consumption, weight and processing power requirements, in most cases, will favor a 2D laser scanner solution. The classification algorithm is based on 2D laser scans where seven essential environment features are associated with signatures in the 2D range readings and classification is done using a combined classifier on extracted features. Introducing detectors for terrain height, roughness, steps, curvature, slope, width and invalid data, the paper formulates a data fusion algorithm and discusses how difficult cases such as graveled terrain in single scans of a fixed 2D laser scanner. This section analyzes the signal features from a 2D laser scanner, and focuses on the ability to obtain sufficient source data for classification and safe navigation. A section then describes the terrain classification with subsections for each of the main classification criteria: Height, roughness, step size, curvature, slope, width and invalid data. A final section presents results from test drives and discusses the performance of the classifier relative to the typical terrain types found in the park. This paper is an extension of [3].

2. Laser scanner data

As the laser scanner is the only sensor to detect objects and traversability, the sensor must be able to see objects, which need to be avoided, sufficiently early to allow the navigation system to take appropriate action. Furthermore, the range data from the road must be of sufficient quality to allow classification.

2.1. Scanner geometry optimization

The scanner position and tilt angle can be determined from the overall robot requirements.

Problem: The robot travels at a speed of \( V \), and a breaking deceleration \( a_b \). The 2D laser scanner is mounted at a height of \( h_L \) and tilted down \( \theta_L \) from horizontal. The laser scanner returns \( N \) range measurements in \( \Delta \) increments with a max range of \( R_s \). The scan rate is \( f_s \). The robot has a time to react \( t_r \), including computational time to detect an obstacle.

Remark: For the commercial laser scanner used, \( N = 181 \), \( \Delta = 1^\circ \), \( R_s = 8 \) m and a maximal scan rate, \( f_s \leq 75 \) s\(^{-1} \).

Determine: The laser scanner geometry \((h_L, \theta_L)\) and scan rate \( f_s \) to ensure:

The robot can brake before it is within a guard distance \( S_g \) from a detected obstacle.

Objects down to a size (diameter) \( D \) can be detected.

Solution: On a flat surface the road detection distance \( S_r \) is determined by the sensor height \( h_L \), and its tilt angle \( \theta_L \), related as:

\[ S_r = \frac{h_L}{\tan \theta_L} \]

The maximum robot speed for a given detection distance is dependent on maximum brake deceleration \( a_b \) and the braking distance \( S_b \):

\[ V_{\text{max}} = \sqrt{2a_b S_b} \]

\[ S_b = S_r - S_g - x_j - V(t_r + f_s^{-1}) \] \( (1) \)

The breaking distance \( S_b \) is shorter than the road detection distance \( S_r \) by: A guard distance \( S_g \), the distance that is required to detect an obstacle \( x_j \), the distance traveled in the reaction time \( t_r \) and the scan rate \( f_s \).

The largest object \( D \) that can remain undetected is:

\[ D = \left( \frac{V}{f_s} + x_j \right) \tan \theta_L \]
Results: For this robot, the smallest object that needs to be avoided has \( D = 5 \) cm. The minimum detect distance \( x_j \) is on average 15 cm (distance from road surface detection to object, as shown on Fig. 2). The maximum brake deceleration is \( a_b = 2 \) m/s\(^2\). The reaction time – until brake condition is effective – is 0.2 s. The guard distance is 0.5 m, of which the bumper takes 0.2 m. The optimal scanner geometry was found to be tilt angle \( \theta_L = 9^\circ \) and \( h_L = 0.41 \) m.

A minimum scan rate of \( f_s = 3 \) scans/s is set to allow performance in non stationary situations at low speed.

By these settings the required scan rate is a function of velocity as shown in Fig. 3. The required scan rate at cruise speed of 1.5 m/s is about 10 scans/s. The maximum robot speed, from Eq. (1), is \( V_{\text{max}} = 2.6 \) m/s.

2.2. Data quality in non-ideal terrain

At the used tilt and height, a flat surface is detected at 2.6 m in front of the robot, and up to about 7.5 m left and right. At 7.5 m left and right the measurement angle between the laser beam and the surface is down to approximately 3\(^\circ\), and the distance between measurements is 0.4 m. If the road is sloped – higher at the center and sloping down either side – the distance between measurements increases further. The road shown in Fig. 1 has 4 m to the other side, and the measurement angle is here 5\(^\circ\) with 15 cm between measurements.

A higher number of measurements per meter provides better quality for the terrain classification, the highest quality is just in front of the robot, with about 22 measurements per meter.

A larger tilt angle would increase detection quality of a sloped road, but increase demand for scan rate to detect small objects. A larger tilt angle would fur-
Assumption 1: Each 3D reading can be categorized as belonging to either of three classes, \( P_i(k) \in \mathcal{C} \), \( \mathcal{C} = \{ \mathcal{C}_t, \mathcal{C}_n, \mathcal{C}_o \} \) where \( \mathcal{C}_t \) : traversable, \( \mathcal{C}_n \) : not traversable and \( \mathcal{C}_o \) : invalid data. Each \( P_i(k) \in \mathcal{C}_t \) will belong to one traversable segment \( S_t(k) \) of the set of traversable segments \( \mathcal{S}_t \) in the scan \( k \).

Assumption 2: Seven main features characterize the natural environment: \( \mathcal{F}_h \) : raw height, \( \mathcal{F}_r \) : roughness, \( \mathcal{F}_z \) : step size, \( \mathcal{F}_c \) : curvature, \( \mathcal{F}_w \) : slope and width, and \( \mathcal{F}_o \) : invalid data. A unique mapping exists \( \mathcal{M}_{CF}(\mathcal{F}) : \mathcal{F} \rightarrow \mathcal{C} \) that categorization can be uniquely determined from. Further a mapping exists \( \mathcal{M}_{SF}(\mathcal{F}) : \mathcal{F} \rightarrow \mathcal{S} \) for measurements in category \( \mathcal{C}_t \).

Testing each measurement \( P_i \) and associating a membership function with each feature, the aim is to determine a classification into traversable and not-traversable segments and let this information navigate the robot. The formal procedure of feature extraction and test of hypotheses about categorization is pursued in the following subsections, starting with a formal statement of the problem. It is a prerequisite that scan readings \( P^L(k) \), are transformed to the appropriate body coordinates \( P(k) \).

\[ \mathcal{F}_i \subseteq \{ \mathcal{F}_h, \mathcal{F}_r, \mathcal{F}_z, \mathcal{F}_c, \mathcal{F}_w, \mathcal{F}_o \} \text{ and } \mathcal{C}_i \subseteq \{ \mathcal{C}_t, \mathcal{C}_n, \mathcal{C}_o \}. \]

**Problem:** Given 2D laser readings \( P(k) \), determine membership of a feature function \( \mathcal{F}_i(P(k)) \) and determine a mapping \( \mathcal{M}_{CF}(\mathcal{F}) : \mathcal{F} \rightarrow \mathcal{C} \) to categorize \( P_i(k) \in \mathcal{C}_i \) and for \( P_i \in \mathcal{C}_t \) a mapping \( \mathcal{M}_{SF}(\mathcal{F}) : \mathcal{F} \rightarrow \mathcal{S} \).

For brevity, and because feature extraction and classification are done on single scans in this context, the scan index \( k \) is omitted in the remainder of the paper.

### 3.1. Invalid data

The laser scanner detects the surface at a small angle, but in most cases the surface is sufficiently rough to get stable range measurement. On smooth surfaces – especially water filled pits and wet asphalt – the laser scanner is often unable to detect the surface.

In these cases the laser scanner returns maximum range, the same value as if the reflecting surface were further away than 8 m.

The feature extraction for invalid data is

\[ \mathcal{F}_o(P^L_t) = \{ d_{inf} \leq d_i \} \quad (2) \]

The limit is set to the maximum range for the laser scanner \( d_{inf} = 8 \text{ m} \).

These measurements need to be disregarded from the classification process.
Fig. 4. The laser measurements from Fig. 5 are shown in measurement order (−90° to 90°) in order to show the roughness estimate at each angle.

3.2. Raw height feature

The feature extraction for valid data starts with the raw height of the measurement \( h(P_i) \) assuming the robot is on a flat surface.

\[
h(P_i) = h_L - x_i \tan \theta_L
\]

\[
F_h(P_i) = \begin{cases} 
  h_{\text{inf}} < h(P_i) < h_{\text{sup}} 
\end{cases}
\]

For the system tested, the upper limit was set to \( h_{\text{sup}} = 0.2 \text{ m} \). This threshold will limit erroneous classification of flat surfaces, e.g., a wall in front of the robot. The lower threshold is sensitive to road curvature in combination with tilt and yaw of the robot in the present application where attitude sensors were not available. The lower limit was set to \( h_{\text{inf}} = -0.5 \text{ m} \) in the experiments.

3.3. Roughness feature

Roughness of data in a 2D laser scan is defined as the square root of local variance of distance to reflections along the scan. A general estimation of local roughness was given in [3] using a singular value decomposition approach. However, this algorithm was too computationally demanding to implement in the embedded software on the robot tested, so an alternative algorithm was developed.

3.3.1. Roughness algorithm

Select a consecutive point set \( P_{n,m} \) covering half a robot width \( W \),

\[
P_{n,m} = \left\{ P_i \in P \middle| \frac{n}{m} \leq i \leq \frac{m}{m} \right\}
\]

where

\[
m_{\text{min}} = \text{MIN}(m) \mid P_m - P_n \geq \frac{W}{2}
\]

Calculate a line \( L_n \) in the \( x, y \) plane as

\[
L_n = \begin{cases} 
  x = a_n + b_n y \\
  a_n = \overline{x} - b_n \overline{y} \\
  b_n = \frac{\sigma_{xy}^2 - \sigma_{yy}^2}{\sigma_{xx}^2} \\
  \sigma_{xy}^2 = \sum (x_i - \overline{x})(y_i - \overline{y}) \\
  \sigma_{yy}^2 = \sum (y_i - \overline{y})^2
\end{cases}
\]

Calculate roughness \( R_n \) in the interval as the average deviation from the fitted line

\[
R_n = \sqrt{\frac{1}{m - n} \sum_{i=n}^{m} (b_n y_i - x_i + a_n)^2}{b_n^2 + 1}
\]

The length of the fitted line of half a robot width was selected to make \( R_n \) sensitive to roughness in the terrain with a size relative to the robot size. Soft curves relative to the robot size will give a small roughness value. An example of the roughness measure is shown in Fig. 4 for the scene from Fig. 1. The roughness is the full line at the bottom, and the corresponding laser scanner measurements in the \( x \)-direction (\( x_i \)) is shown above.

3.3.2. Roughness groups

The intention is to group measurement into traversable segments. If there are more types of traversable segments, these should be grouped separately. An ex-
ample of traversable segment types could be an asphalt road edged by cut grass, both segment types are traversable, but it would – in most cases – be preferable for the robot to keep to the asphalt. This is accomplished in three steps. First the measurements are divided into homogeneous groups (using raw height and roughness). These groups are then combined using the classifiers for step size $F_s$ and curvature $F_c$. Lastly the resulting groups are filtered based on slope and width $F_w$ to a set of traversable segments $S$.

Neighboring traversable points $P_i$ in $P_n$ to $P_m$ are said to belong to group $G_j$ if their roughness value $R_i$ are relatively homogeneous as defined in Eq. (7).

$$G_j = \left\{ P_i \in P_{n,m} | \begin{align*} & h_{inf} < z_i < h_{sup} \\
& \land R_i < R_{sup} \\
& \land E(P_{n-1}, L_n) < R_{lim} \\
& \land E(P_{m+1}, L_n) < R_{lim} \end{align*} \right\}$$

where

$$E(P_i, L_n) = \frac{|y_i - z_i + a_n|}{\sqrt{b_n^2 + 1}}$$

$$R_{lim} = \alpha \text{MIN}(R_i | P_i \in P_{n,m})$$

This implements an adaptive threshold based on the point with the minimum roughness in the interval. The interval is then expanded to the point where the distance to the next measurement is above the adaptive threshold. The distance $E(P_i, L_n)$ is taken from the next measurement $P_{m+1}$ or $P_{n-1}$ to the fitted line $L_n$ used to calculate $R_n$. The threshold limit $R_{lim}$ is set to $\alpha$ times the minimum roughness inside the interval.

The value for the roughness threshold $R_{lim}$ was found experimentally to $\alpha = 4.5$ by optimizing for large group size and to avoid combination of different terrain types.

Finally, association of a point to the feature $F_s$ is obtained as

$$\forall j : F_s(P_i) = P_i \in G_j$$

Figure 4 is an example of the resulting grouping, using data from the asphalt road with rough grass edges shown in Fig. 1. The groupings are shown below the laser measurements. The groupings include the asphalt area (from about $-50^\circ$ to $20^\circ$), as well as a number of shorter segments in the rough grass left and right. The asphalt area has a very low roughness (less than 0.01 m), but aligned measurements, with a roughness below the hard threshold of $R_{sup}(0.1 \text{ m})$, are also found in the road shoulder area.

3.4. Step size

The surface of graveled roads and areas are often a combination of smooth areas separated by smaller objects like stones or tracks. The adaptive threshold typically separates such intervals. Branches, leaves and stones also tend to break up otherwise smooth roads into separate segments.

The produced groups are therefore inspected and flagged for possible combination if they are likely to be from the same surface and the area between the groups is traversable.

The step size feature ensures that two segments are not combined if they are separated by an obstacle, or separated in height. I.e. a sidewalk should not be combined with the road. Included in the step size feature $F_s$ is also a step in roughness, as defined in Eq. (9).

$$F_s(P_i) = \left\{ \begin{align*} & \begin{array}{l} p - m \leq 4 \\
& \land 0.5 < \frac{R_k}{R_{k+1}} < 2 \\
& \land |x_m - x_p| < 0.15 \end{array} \\
& p \geq m \\
& P_i \in G_j \\
& P_i \in G_{j+1} \\
& P_i \in G_{j+1} \\
& p > m \\
& P_i \in G_{j+1} \\
& |\overrightarrow{y_p}| < 0.15 \\
& \text{where} \\
& \overrightarrow{y_p} = \frac{x_m + x_p}{2} \end{align*} \right\}$$

This step criteria allows groups to be separated by up to 3 measurements, as long as these measurements points $P_{m+1}$ to $P_{p-1}$ are not too far away (15 cm) from the average of the two endpoints. The groups may not be combined if the roughness $R_k$ and $R_{k+1}$, associated with groups $G_k$ and $G_{k+1}$, differ by more than a factor 2. The $x$ difference between the near endpoints of the groups may be separated by no more than 15 cm (corresponding to a difference in height of 2.5 cm with the sensor tilt angle chosen).

3.5. Curvature

A curvature criteria ensures that a road with a high convex profile can be classified as one traversable segment, whereas concave profiles that often describes a ditch cannot.

The feature $F_c$ defined in Eq. (10) checks for curvature and allows combination of two groups $G_j$ ($P_i \in P_{n,m}$) and $G_{j+1}$ ($P_i \in P_{p,q}$) based on the ver-
Fig. 5. The laser measurements from Fig. 1 are shown relative to the robot. The road is the smooth slightly curved part.

Fig. 6. On relatively flat gravelled terrain the traversable area is divided into a number of roughness groups, as shown below the measurement points. These groups are then combined to one traversable segment (shown above the measurement points). An \((x, y)\) projection is shown in Fig. 7.

3.6. Slope and width

Consecutive groups formed by points that possess the features \(F_s\) and \(F_c\) are combined to one group \(G_j\). All groups \(G_j\) must further fulfill a combined slope and width criterion to become fully qualified traversable segments \(S_j\).

The slope of a traversable segment must be less than \(\Delta_{yz} = 10^\circ\) vertically (in the y-z plane), and the width of a traversable segment must be wider than the robot.

\[
F_w(P_i) = \begin{cases} 
    P_i \in G_j & |P_m - P_p| > W \\
    P_i \in G_{j+1} & A_j < \Delta_{sup} \\
    p > m & A_j - A_{j+1} < \Delta_{inf}
\end{cases}
\]

where (10)

\[
A_j = \tan^{-1} \left( \frac{z_m - z_q}{y_m - y_q} \right)
\]

\[
A_{j+1} = \tan^{-1} \left( \frac{z_q - z_p}{y_q - y_p} \right)
\]

An example of this group combination and prohibited combination can be seen in Figs 8 and 9, where the high profile road is crossed by a horse track. The horse track is separated from the road, but both parts are smooth enough to be classified traversable.

3.7. Single scan classification

The classification of points of the single laser scan are finally obtained as...
Fig. 8. Data from graveled road crossed by a horse track. The road is the area with the high profile (about 15 cm higher at the center). On both sides are relatively flat areas from the horse track. Rough grass on the path edges before the horse track is just visible left and right of the robot. The segmentation details are shown in Fig. 9.

$$C\Omega(P_i) = F\Omega(P_i)$$
$$C_l(P_i) = F_h(P_i) \cap F_r(P_i) \cap F_s(P_i) \cap F_c(P_i) \cap F_w(P_i)$$

$$C_n(P_i) = \overline{(C_l(P_i) \cup C\Omega(P_i))}$$

The formation of traversable segments from the defined groups are

$$S_j = F_w(P_i \in G_j)$$

These steps define the solution to the terrain classification problem.

4. Results

The classification algorithm has been tested on a set of available paths in the Danish national park. The park has been traversed autonomously – a distance of more than 3 km – using this classification as the main tool to stay on the roads and avoid obstacles.

A few typical classification results are shown in Figs 4 through 9.

Figure 5 (with roughness in Fig. 4) shows a smooth asphalt road, where the initial grouping of measurements into homogeneous segments classifies the road in one go.

Figures 6 and 7 show an area where the robot is crossing a graveled road. Here the laser scanner can see only the road surface. Therefore all laser returns should be classified as traversable. The figure shows that the surface is relatively flat. The roughness grouping has divided the area into 6 groups (shown below the measurements in Fig. 6), but all of these are recom-bined into one traversable segment (shown above the measurements).

Figures 8 and 9 show data from a graveled road with a horse track crossing. The laser scanner just sees the path edges (left and right of the robot in Fig. 8) before the horse track, and sees the horse track itself as flat areas left and right of the profiled road. The center of the road is about 15 cm higher that its edges. The algorithm separates the road from the horse track, and marks both as traversable. The main criteria here, preventing combination of the path with the horsetrack,
Fig. 11. The transition from asphalt road to graveled area used in Fig. 10. The road shoulder left and right are often sufficiently smooth to allow formation of additional traversable segment on either side of the main road segment.

is $\mathcal{F}_c$ that prevents concave segments (where the road meets the horse track) from being combined.

If the transition from the path to the horse track had been smoother, the segmentation would be more likely to combine the path and the horse track into one traversable segment.

A longer sequence of road classifications are shown in Fig. 11 where the robot leaves the asphalt road shown in Fig. 11 and enters a graveled area in front of the building. The segments selected by the navigation process are shown as solid (blue) lines. The laser measurements classified as not traversable are shown as (orange) dots merging into solid areas.

4.1. Quality

A representative part of the three main types of the traversable terrain were manually analyzed, to assess the quality of autonomous categorizations. Results are shown in Table 1.

On the asphalt road – in Figs 1 and 11 – the classification process found the road in 100% of all cases, 2% were too short (shorter than 4.4 m on a 4.8 m wide road), and 2.7% too long (extended into the road shoulder), but none gave rise to unnecessary maneuvers. On average about 2 extra traversable segments were found each scan, these are mostly found in parts of the grass near the road. These are however discarded by the navigation layer due to their position and roughness (the traversable segment formed by the road has higher priority). 300 laser scans were analyzed covering about 100 m.

On the graveled area on the used route (the upper part of Fig. 10) a traversable area were always found, but 6% of the scans were too short – defined as less than 4 m from robot – of which 2 gave rise to minor unnecessary maneuvers. 120 laser scans were analyzed covering about 40 m.

The graveled road was about 4 m wide and its edges were more rough than the asphalt edges. The graveled road could always be found, but at times (8%) split into smaller segments, of which 2 gave rise to minor unnecessary maneuvers. 300 laser scans were analyzed covering about 100 m.

5. Conclusion

The algorithm described in this paper classified single scan laser data into traversable segments and non-traversable points. The traversable segments represent surface that should allows passage, such as roads.

Roughness was calculated as the average deviation from a best-fit line over an equidistant part of the laser scan. The measurements that fulfill a height criteria and an adaptive roughness criteria were grouped. Hypothesis testing and final classification was done using roughness, step size, slope and width.

The laser scanner was tilted down to allow range measurements from the road surface. A tilt angle of $9^\circ$ allowed sufficiently good road detection to ensure
smooth navigation, even in the sloped and uneven terrain used for tests. The sensor position and scan rate, in combination with the classifier, was shown to allow detection of obstacles of sizes that the robot should avoid.

Results from a national park showed the classifiers ability to detect passable roads sufficiently reliable to allow uninterrupted autonomous navigation. The robot has traversed the park multiple times using the described method as the main datasource for navigation and obstacle avoidance.

A vision system could improve the road and object detection beyond the 2.6 m range covered by the laser scanner, and possibly improve distinction between road and grass, but the paper has shown the 2D laser scanner measurements and appropriate methods for classification cope well with the terrain classification task.

References


