TERRAIN CLASSIFICATION FOR OUTDOOR AUTONOMOUS ROBOTS USING SINGLE 2D LASER SCANS

Robot perception for dirt road navigation

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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 four distinctly different classifiers: raw height, step size, slope, and roughness. Input is a single 2D laser scan and output is a classification of each laser scan range reading. The range readings are classified as either returning from an obstacle (not traversable) or from traversable ground. Experimental results are shown and discussed from the implementation done with a department developed Medium Mobile Robot and tests conducted in a national park environment.

1 INTRODUCTION

Safe autonomous navigation in unstructured or semi-structured outdoor environments presents a considerable challenge. Solving this challenge would allow applications within many areas such as ground-based surveillance, agriculture, as well as mining.

To achieve this level of autonomy, a robot must be able to perceive and interpret the environment in a meaningful way. Limitations in current sensing technology, difficulties in modelling the interaction between robot and terrain, and a dynamically changing unknown environment all makes this difficult.

Imperative for successful and safe autonomous navigation is the identification of obstacles which either can be damaged or hurt, or in turn can disable or cause damage to the robot. Analogous to this it must also be possible to identify traversable terrain (e.g. the road). Bertozzi and Broggi (1997) argues that this problem can be divided into *lane following* and *obstacle detection*. This paper concentrates on the detection of obstacles.

Much current work in laser scanner classification tends to focus on using 3D laser scanners, vision or a combination of 3D laser scanners and vision. Vandapel (2004) used a 3D laser scanner to classify point clouds into linear features, surfaces, and scatter. Classification was based on a learnt training set. Montemerlo and Thrun (2004) identified navigable terrain using a 3D laser scanner by checking if all measurements in the vicinity of a range reading had less than a few centimetres deviation. Wallace et al (1986) used a vision-based edge detection algorithm to identify road borders. Jochem et. Al (1993) followed roads using vision and neural networks. Macedo et al (2000) developed an algorithm that distinguished compressible grass (which is traversable) from obstacles such as rocks

Figure 1: The robot platform tested in the dirt-road semi-structured environment from a Danish national park

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using spatial coherence techniques with an omni-directional single line laser.

Wettergreen et al (2005) extracted three metrics from stereovision data and used these to traverse a rock field. Iagnemma et al (2004) followed quite another route and proposed a tactile and vibration-based approach to terrain classification.

This paper proposes a terrain classification algorithm that discriminates between obstacles and traversable terrain using a fixed 2D laser scanner as the main sensor. This is notoriously harder than using 3D sensor inputs as there is much less information available.

In the classification algorithm proposed here, four essential environment features are associated with signatures in the 2D laser scan range readings, and classification is done using a combined classifier on the extracted features. The salient features looked at are: terrain height, terrain slope, increments in terrain height, and variance in height across the terrain.

This work is a contribution towards demonstrating that it will become feasible to achieve autonomy over long distances (>4km) in a natural outdoor terrain using only a 2D laser scanner for terrain classification.

The paper shows results of testing the classifier on the Medium Mobile Robot (MMR) platform from the Technical University of Denmark on various paved and dirt roads in a national park (see Figure 1). The quality of classification is discussed for different cases of natural environment encountered in the tests. The contribution of the paper is to demonstrate that the proposed classification techniques suffice to navigate the MMR safely and to demonstrate that the proposed method is robust to the variation encountered in the natural environment using simple equipment: 2D laser scanner, a cheap commercial GPS sensor and odometry.

2 TERRAIN CLASSIFICATION

The terrain classification algorithm combines four distinctly different terrain classifiers: raw height, step size, slope, and roughness.

Input for each run of the algorithm is a single laser scan. Output as stated in the *Introduction* is a classification for each range reading as returning from either an obstacle or as traversable terrain. The terrain classifiers all work on point statistics.

2.1 Coordinate System

On the MMR the laser scanner is tilted at 8° down towards the ground and gives 180 range readings in a 180° frontal arc. Only the range readings in a 120° arc in front of the robot were used for terrain classification as this approximately corresponds to which range readings would hit the ground with the given scanner tilt.

Each laser scan range reading is converted to a 3D point expressed in the vehicle frame. The vehicle stands in (0, 0, 0). Assuming the robot is standing on level ground then up (height) is the Z-axis in the positive direction. The robot looks out the positive Y-axis, and the X-axis increases towards the right of the robot. The raw height and step size classifier only look at the height (Z-axis).

In the following sections P will denote a set of range readings converted to 3D points. The hypothesis is that each 3D point can be mapped to either belonging to an obstacle or traversable terrain. This is explained in Eq. (1).

$$\begin{aligned} &H(obstacle) \subseteq P \\ &H(traversable) = P \setminus H(obstacle) \end{aligned} \tag{1}$$

A single element of P is denoted p_i where i represents the range reading angle (inside the 180° frontal arc). The coordinates of a point are given by $p_i = (p_{ix}, p_{iy}, p_{iz})$. The conversion from range readings to 3D coordinates is shown in Eq. (2). $range_{\mathrm{i}}$ is the measured range at angle i. θ_{tilt} is the angle the laser scanner is tilted (in our case 8°). S_{height} is the height the laser scanner is mounted at relative to the plane of the robots wheel-base (on the MMR this is 0.41m).

$$\begin{aligned} &px_i = range_i * \cos(i) \\ &py_i = \cos(\theta_{tilt}) * range_i * \sin(i) \\ &pz_i = \sin(\theta_{tilt}) * range_i * \sin(i) + S_{height} \end{aligned} \tag{2}$$

2.2 Raw Height

This classifier looks at the height of each range reading (point) in the vehicle frame. If a point is higher or lower (on the Z-axis) than a value decided by a height threshold then the point is labelled as returning from an obstacle. In the tested system if a point had a height of ±20cm it was labelled as an obstacle. In practice its purpose is to identify obstacles such as people, tree trunks and pits. Obstacles inside the ±20cm thresholds cannot be detected. The robot has no sensors to measure pitch and yaw of the laser scanner relative to the ground surface. As such, the height thresholds are chosen to allow for variations in measured height of the ground due to lack of attitude determination. The classifier is shown in Eq. (3) where $height_{max}$ and $height_{min}$ are the height thresholds.

$$H(obstacle) = \left\{ p_i \in P \middle| \begin{array}{l} p_{iz} > height_{\max} \\ \vee p_{iz} < height_{\min} \end{array} \right\} \quad (3)$$

Here, the threshold $height_{\min} < 0$ enables detection of non-traversable cavities in the ground.

2.3 Step Size

A step size classifier looks at the difference in height between neighbouring points where neighbouring is defined as a range within 1° of the specific point. If the difference in height is higher than a threshold (here 5 cm) a terrain step is detected that is too high for the robot to traverse. The algorithm labels both points that form the border between the step as obstacles. As it only looks at the step size, neighbouring points from an obstacle with similar height may be erroneously labelled as traversable. The 5 cm threshold was set based on the robot's physical specifications, the limiting factor being that the front wheel cannot reliably climb anything taller. The classifier is shown in Eq. (4) where $step_{max}$ represents the threshold for difference in height.

$$H(obstacle) = \left\{ p_i \in P \middle| \begin{array}{l} \left| p_{iz} - p_{(i-1)z} \right| > step_{\max} \\ \vee \left| p_{iz} - p_{(i+1)z} \right| > step_{\max} \end{array} \right\} \quad (4)$$

2.4 Slope

Slope classification aims at identifying terrain which has too high an incline to be traversed. The classification is done by calculating a 2D line fit using least squares around a point sample. For each point, the neighbouring points within ±2° are used. The least squares line is then calculated using the X and Z-axis values. The point examined is subsequently classified based on its slope. If exceeding a limit $slope_{max} = \pm 0.1$ it is classified as belonging to terrain that is too steep for the robot and is labelled as an obstacle. The assumption here is that the best-fit line approximates the steepness of the terrain around this point sample. The value of ±0.1 was chosen for two reasons. First, it represents what the robot can physically handle. Secondly, it keeps the robot on reasonably level ground where lack of attitude determination is less critical. The classifier can be seen in Eq. (5) where $slope_{max}$ is the slope threshold.

$$\begin{array}{l} given: \\ A = \begin{bmatrix} p_{(i-2)x} & p_{(i-2)z} & 1 \\ \vdots & \vdots & \vdots \\ p_{(i+2)x} & p_{(i+2)z} & 1 \end{bmatrix} \text{ and} \\ \text{a singular value decomposition} \\ A = UDV^T; \;\; U^TU = V^TV = I; \\ \left[c_1, c_2, \ldots c_n\right]^T = \text{last column of } V; \\ let: \\ a = -\frac{c_1}{c_2}; \\ calculate: \\ H(obstacle) = \left\{ p_i \in P \middle| |a| > slope_{\max} \right\} \end{array} \quad (5)$$

2.5 Roughness

The roughness classifier looks at the variance in height in the vicinity of a specific point. The purpose is to identify areas with low variance as these areas are more likely to be easily traversable. For example, heavy underbrush in a forest may have a high variance; a flat road will appear as a region of points with a low variance. Trend removal is also essential as a slightly sloping surface relative to the vehicle frame may give a high variance in height relative to the zero height plane {Z|Z=0}. The variance in height is hence calculated relative to a 2D best-fit line. This line is calculated in the same manner as in the slope classifier. The variance is then calculated as the shortest distance from each point (using again the two neighbouring points on either side of the point) to the best-fit line using only the X and Z-axis coordinates. If the variance in a point sample in this method was found to be larger than $variance_{max}$ = 2.5e-10 the point was labelled as an obstacle. This classifier can give more accurate results than the other classifiers (see Table 1) but it cannot stand alone since, for example, a flat wall obstacle would return a low variance. The value of the variance threshold was tuned based on several kilometre long recorded datasets from the national park environment (along both paved as well as dirt roads). The roughness classifier algorithm is shown in Eq.(6).

$$
\begin{aligned}
&given: \\
&A = \begin{bmatrix} p_{(i-2)x} & p_{(i-2)z} & 1 \\ \vdots & \vdots & \vdots \\ p_{(i+2)x} & p_{(i+2)z} & 1 \end{bmatrix} \text{ and} \\
&\text{a singular value decomposition} \\
&A = UDV^T; \;\; U^T U = V^T V = I; \\
&[c_1, c_2, \ldots c_n]^T = \text{last column of } V; \\
&\text{let } X,\ Z,\ E \text{ be } 1^{st}, 2^{nd} \text{ and } 3^{rd} \text{ column of } A, \\
&\text{respectively and} \\
&D = \frac{1}{k}\left(c_1 X + c_2 Z + c_3 E\right); \\
&let: \\
&\sigma^2 = \frac{1}{5\text{-}1} D^T D \\
&calculate: \\
&H(obstacle) = \left\{ p_i \in P \,\middle|\, \sigma^2 > \text{variance}_{\max} \right\}
\end{aligned}
\tag{6}
$$

2.6 Combining Classifiers

A combined classifier is created by running the terrain classifiers in the sequential order: raw height, step size, slope, and then roughness. Initially all points are labelled as traversable. If a point is classified as an obstacle by one of the classifiers it is not further attempted classified in the subsequent classifiers. Once all the classifiers have been run, points that lie in gaps between obstacles which are too narrow to allow the robot to traverse are labelled as obstacles. The gap size is calculated using the Euclidean distance between the obstacles in the XY plane. As raw height and step size are computationally less expensive than the two other classifiers, it is computationally favourable to classify points between obstacles as non-traversable early in the algorithm.

3 EXPERIMENTAL RESULTS

The quality of the classification was tested using a dataset of 30 laser scans taken using the MMR travelling autonomously 200m along a forest dirt road (see Figure 2). The laser scans have been sampled at regular intervals along the 200m run. Each of the points in the laser scans have been manually classified as belonging either to traversable terrain (the dirt road) or obstacles. This manual classification was done to establish a ground truth. The laser scans were compared to photographs and time-stamped GPS/odometry data. In certain situations along the forest dirt road, there was ambiguity in what constituted the edge of the road. In these cases, if the terrain appeared navigable from photographs it was assumed to be so.

Each of the separate classifiers that compose the combined classifier was tested individually along with the combined classifier. The number of misclassifications compared to the manual classification was recorded and results are summarised in Table 1. The results clearly show that there is significant benefit in combining the different classifiers.

A quality assessment is made using two measures: p_{missed}^{any} the probability of missed detection of an obstacle by any single classifier; p_{missed}^{all} the misclassification of traversable road by combining all available classifiers.

The measure of missed detection by any of the classifiers is

$$
\begin{aligned}
&p_{missed}^{any} = \\
&prob\left\{ \begin{matrix} \exists p_i \in \{obstacle\} \,| \\ \exists \; classifier : H(p_i) = H(traversable) \end{matrix} \right\}
\end{aligned}
\tag{7}
$$

Such misclassification for the individual classifiers was found to be as high as $(p_{missed}^{any} > 95\%)$.

The probability of misclassification of traversable points p_{missed}^{all} when combining all classifiers is

$$
\begin{aligned}
&p_{missed}^{all} = \\
&prob\left\{ \begin{matrix} \forall p_i \in \{traversable\} \,| \\ \forall \; classifier : H(p_i) = H(obstacle) \end{matrix} \right\}
\end{aligned}
\tag{8}
$$

The misclassification for the individual classifiers was found to be as low as $(p_{missed}^{all} < 5\%)$.

The detailed results in Table 1 show that although raw height, step size, and slope all misclassify around half the points on their own, they can still enhance the combined classifier. This is because they detect different types of obstacles. For example, raw height only looks at the obstacles height whereas step size only detects changes in height. In the Combined (with gap removal) classifier the 4.4% misclassifications have proven to be acceptable in practice as often it is just small parts of the road which are mislabelled as obstacles (the robot simply navigates around the suspicious terrain).

Table 1: Experimental results from the classifiers

Classifier	Misclassifications	Percentage misclassified
Raw height	2334	64.8%
Step size	2156	59.9%
Slope	1657	46.0%
Roughness	663	18.4%
Combined	393	10.9%
Combined (with gap removal)	157	4.4%

4 SUMMARY

A classifier fusion algorithm was proposed that enable a mobile robot to locate and travel along a safe path in a natural environment using a 2D laser scanner, a civil GPS receiver and odometry.

Although performance of individual classifiers, based on simple single scan statistics, was not impressive, the combined set of classifiers were found to perform quite accetably in classifying a dirt road from surrounding terrain with less than 5% of scanned points being misclassified. The performance was documented in a natural environment. This work has shown that 2D laser scans can give considerable information about a semi-structured natural environment.

Ongoing work includes maintaining an estimate of the roads position across the trajectory of multiple robot positions and using this information in the classifier. Also, quantifying the accuracy of a given classification without ground truth is being looked into. Lastly, attempts are being made to detect the type of road surface currently being navigated on. This may allow for adaptive tuning of classifiers by making the thresholds in the hypothesis tests dependant on the road surface.

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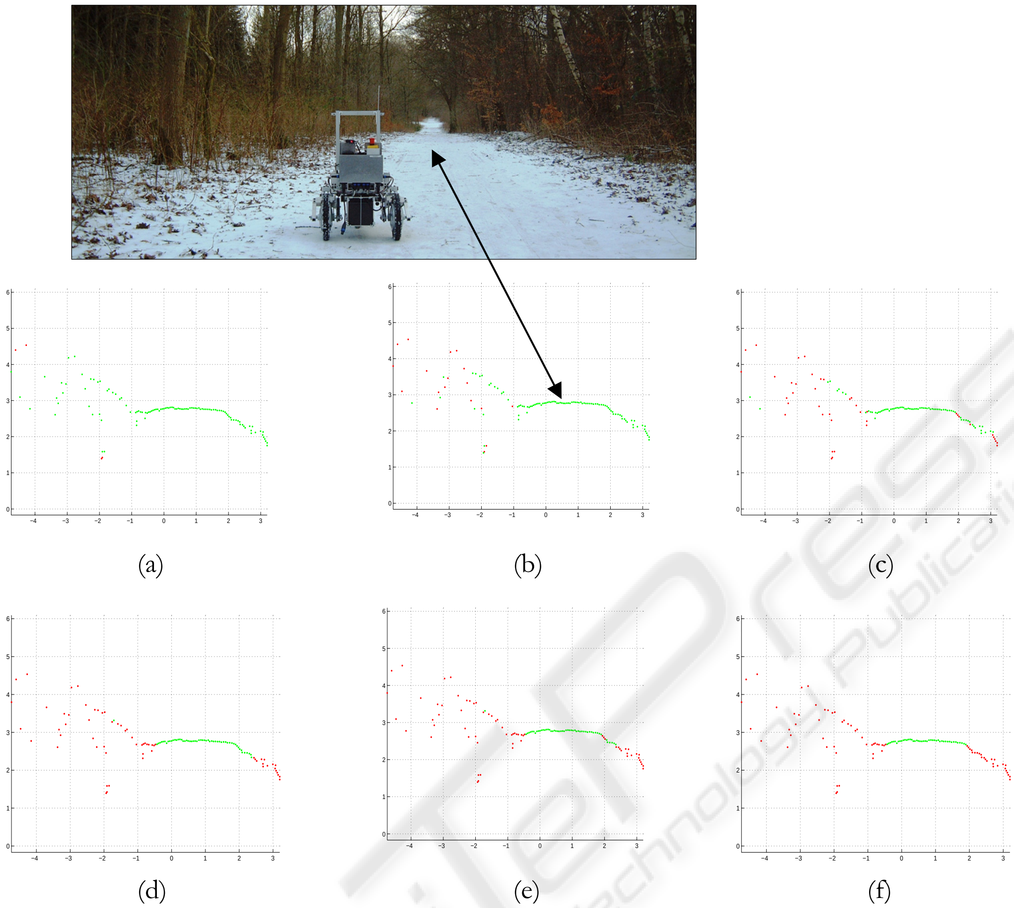

Figure 2: Results of different terrain classifiers on a single laser scan (Y-axis is up and the X-axis increases to the right). A photograph shows roughly where the robot was standing. A double arrow shows how the road in the photograph corresponds to its location in the laser scan. The labels are (a) raw height, (b) step size, (c) slope, (d) roughness, (e) combined, and (f) combined with gap removal. Red points represent obstacles and green points the traversable terrain