Road Terrain Type Classification based on Laser Measurement System Data

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Abstract

For road vehicles, knowledge of terrain types is useful in improving passenger safety and comfort. The conventional methods are susceptible to vehicle speed variations and in this paper we present a method of using Laser Measurement System (LMS) data for speed independent road type classification. Experiments were carried out with an instrumented road vehicle (CRUISE), by manually driving on a variety of road terrain types namely Asphalt, Concrete, Grass, and Gravel roads at different speeds. A looking down LMS is used for capturing the terrain data. The range data is capable of capturing the structural differences while the remission values are used to observe anomalies in surface reflectance properties. Both measurements are combined and used in a Support Vector Machines Classifier to achieve an average accuracy of 95% on different road types.

1 Introduction

Road terrain type classification based on on-board sensors can provide important, sometimes crucial information regarding safety, fuel efficiency and passenger comfort. It can be used to estimate various physical quantities including friction coefficients, slip angles and vehicle handling characteristics [Iagnemma, 2004] [Nohse, 1991] [Shmulevich, 1996]. Therefore estimation of road surface parameters is of interest in many mobile vehicle applications.

Road terrain type classification methods have been extensively studied in the past. Algorithms based on various sensory modules, such as Laser Measurement Systems, cameras, accelerometers, GPS, and wheel encoders have been reported. Being one of the most reliable sensors, LMS is used in autonomous robots for avoiding dangerous paths [Stavens, 2006] [Dahlkamp, 2006] altogether.

Apart from range information provided by LMS, remission information of the laser beam is also available in some types of laser models. The method in [Wurm, 2009] has been reported to use laser remission values to identify vegetation on structured environments. The approach in [Saitoh, 2010] proposed a method to define a hazard and un-drivable area by using self-supervised learning based on the remission value of a map. However, these two methods find drivable regions but not the road terrain types.

Varieties of road terrain types have abundant different characteristics. Vehicle vibrations while driving on such surfaces could be thought as the most naïve data to be used for identifying different road terrain types [Brooks, 2005] [Komma, 2009]. Weiss et al [Weiss, 2007] used a vertically mounted accelerometer on the platform, RWI ATRV-Jr to classify some indoor and outdoor terrain types. Then the study extended to use an accelerometer and a camera for improved terrain type classification [Weiss, 2008]. Hsiao et al [Hsiao, 2009] and Helmick et al [Helmick, 2009] used images from cameras pointing down for road terrain type classification. The images were analysed to identify potholes and ruts to distinguish different road terrain types. However, both of the research works were based on small sized robotic platform operating at slow speeds. The stability of this method was affected by lack of camera's exposure time to capture fast moving features or low illuminated backgrounds [Wang, 2011].

The approaches mentioned above are

implemented on small sized robotic platforms that have rigid wheels providing a good coupling between the terrain and the rover. Those methods cannot be readily used in road vehicles due to various dampers including the tyres and shock-absorbers. Therefore, in [Ward 2009], they utilized the dynamic model of the vehicle with a vertically mounted accelerometer to reconstruct the road surface. As the road surface is independent of the vehicle speed, frequency domain features were extracted for terrain type classification. However, further research [Wang, 2012] showed that it has limitations due to non-ideal nature and parametric uncertainties of the model resulting in speed dependency.

This paper focuses on road terrain type classification using LMS, which provides range and remission values at a high sampling rate. Thereby, spatial frequency features of the lateral direction can be extracted for road terrain classification.

The paper is arranged as follows. Section 2 describes the road surface estimation procedure and the feature extraction methodology. Section 3 presents the details of the classifier and in Section 4 experimental platform is described followed by experimental results. Section 5 concludes the paper indicating future direction of the research.

2 Methodology

2.1 Geometric Arrangement of the LMS

A downward-looking SICK LMS111 is mounted on the CRUISE as shown in Fig. 1. It scans the road surface vertically in a two dimensional plane at a 50 Hz sampling rate. The LMS has a 270° field of view with 0.5° angular resolution providing 541 range and remission values per scan. While the vehicle is moving forward, it leaves a trace of three dimensional point cloud of the surface.

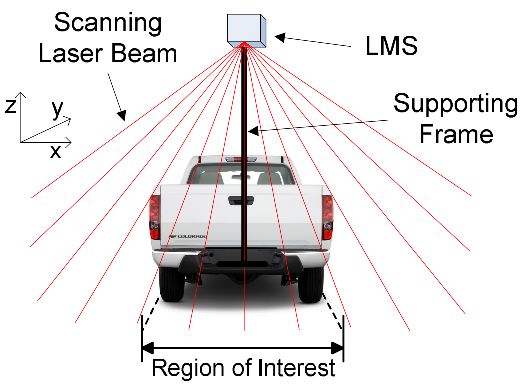


Fig. 1 The geometric arrangement of the LMS

2.2 Reconstruction of the Road Surface

It is well known that the laser beam emitted in a LMS is deflected using a rotating mirror and scans surroundings in a circular manner. In general, once a laser beam incidents on a surface, the light is reflected. This reflected energy can be partly received by the photodiode in the LMS calculating the range to an object based on time of flight measurements.

As shown in Fig. 2, the surface is estimated by the laser range data and the speed data coming from the GPS unit.

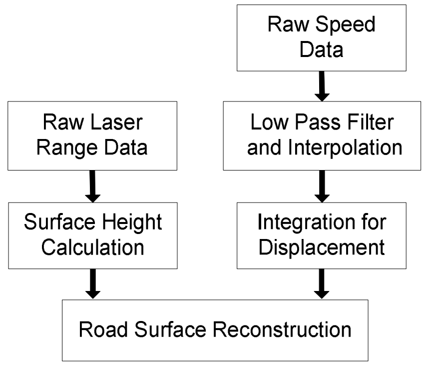


Fig. 2 Reconstruction of the Road Surface

Range Data Processing

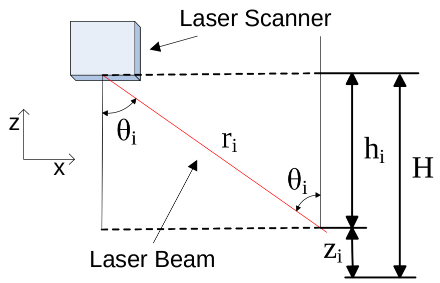


Fig. 3 Mounting geometry of the LMS

Vertical coordinate, z_i, of each range measurement can be easily reconstructed by (See Fig. 3):

$$z_i = H - r_i \cos(\theta_i) \tag{1}$$

where, r_i is laser range value, θ_i is included angle between the current laser beam and z axis, and H is the reference height from a relatively flat floor to the height of the LMS. In a similar way, the x-axis coordinate can be calculated as:

$$x_i = r_i \sin(\theta_i) \tag{2}$$

The 270° scanning field of view contains road surface as well as other nearby objects. Therefore, as illustrated in Fig. 1, a 1.3m wide region of interest is defined for the purpose. This leads to inter-distance between two sampling points of a particular scan to approximately be 2 centimetres on a road surface with the mounted height 2.2 meters of the LMS.

Speed Data Processing

The 20Hz Global Positioning System (GPS) on board is used to measure the speed of the vehicle. Although the experiments were restricted in open outdoor areas, the GPS did not keep a clear and stable logging all the way for some unknown reasons. At some places, the logged speed data contained unreasonable errors, so a low pass filter was employed to remove them.

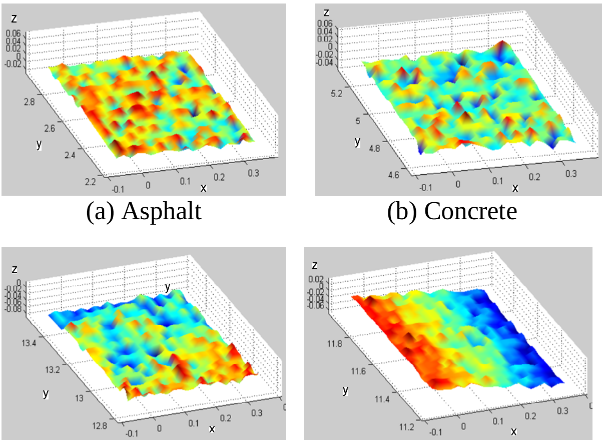
As the speed data rate was too slow when comparing with that of the LMS data, it was interpolated to 50 Hz by proximal interpolation method (also known as nearest-neighbour interpolation) [Watson, 1984]. Then, simply the longitudinal vehicle displacement, *y(t),* is estimated by,

$$y(t) = \int_0^t |v(t)|\,dt \qquad (3)$$

where *v(t)* is the estimated vehicle speed.

Road Surface

Once the data is processed to estimate the longitudinal and lateral displacements of the laser data point clouds, a three dimensional view of the displacements can be generated. Such displacement profiles of the road types are shown in Fig. 4. It seems not difficult to reconstruct a qualitative assessment of the plots for the differences purely by visual inspections.



(a) Asphalt (b) Concrete

(c) Grass (d) Gravel

Fig. 4 Three dimensional surface data of four different road types.

2.3 Feature Matrix

Extraction of Spatial Frequency Features

The estimated 3D surface has more dissimilarity in the resolution along the vehicle moving direction due to the variations of the speed. However, the vehicle speed has minimal effect on the lateral data. Therefore, in this work, only the lateral components are considered. Rather than relying on each new lateral scan of data, this will concatenate a group of scans captured over the vehicle length, which is 4 metres. This is done for future comparisons with other sensor modalities. The number of scans depends on the vehicle's speed, however, in general, it is around 35~145 scans at speeds of 20~80 km/h.

The feature matrix is formed by carrying out the Fast Fourier Transform on each scan. The power spectral density (PSD) is then calculated using Welch's method [Welch, 1967]. The start frequency, end frequency and frequency step are empirically decided as 0 cycles/meter (c/m) to 35 c/m with 0.1 c/m interval, which led to optimal classification rate in many prior tests.

$$F = \begin{bmatrix} F_{s_1,f_1} & \cdots & F_{s_n,f_1} \\ \vdots & \ddots & \vdots \\ F_{s_1,f_m} & \cdots & F_{s_n,f_m} \end{bmatrix} \qquad (3)$$

Then the PSD of each group of scan, which defines the feature vector, is arranged column by column to form the feature matrix *F*, given in (3). In this matrix, every column refers to a feature vector (a group of scanning lines) while every row represents the features (PSD) extracted using the above procedure. For instance, in this case, F_{s_1,f_1} presents the PSD from 0 c/m to 0.1 c/m of the 1st group lines, while F_{s_n,f_1} presents the PSD from 0 c/m to 0.1 c/m of the nth group, and F_{s_n,f_m} presents the PSD from 34.5 c/m to the end 35 c/m of the n^{th} segment. Overall, the matrix, *F* contains *n* samples while each sample has *m* features. Each value of element in matrix (3) indicates a power at a particular investigated frequency forming the final feature matrix. After all it is normalized to reflect each row of *F* mapped to [0, 1].

Remission based Features

As introduced in [Wurm, 2009] and [Saitoh, 2010], a laser remission value is a function of distance, incidence angle and material. For our application, since the LMS is mounted on a frame above the vehicle and the fact that we are only interested in a small field of view, the factors of distance and incidence angle can be considered relatively constant. Therefore, the remission value seems informative for road surface classification.

Similar to the previous section, we segment scanning lines into groups with the same length, however rather than the range values means of the remission values are used. So the feature matrix is,

$$R = \begin{bmatrix} R_{s_1,r_1} & \cdots & R_{s_n,r_1} \\ \vdots & \ddots & \vdots \\ R_{s_1,r_m} & \cdots & R_{s_n,r_m} \end{bmatrix} \qquad (4)$$

As given in the matrix (4), each column refers to mean values of a group (a sample) of lines while each row represents the mean value of a specific angle. For instance, R_{s_1,r_1} presents the mean remission value of all first points of the lines belong to 1st group, while R_{s_n,r_1} presents the mean remission value of all last points of the lines belong to 1st group, and R_{s_n,r_m} presents the mean remission value of all last points of the lines belong to n^{th} segment. The matrix is finally normalized to reflect each row of *R* mapped to [0, 1].

2.4 Classification

A number of classifiers were evaluated. Comparing with Neural Network classifier and Naïve Bayes classifier, Support Vector Machines (SVM) presents the best classification accuracy for road terrain type classification task by several number of off-line tests. SVM conceptually finds a hyper plane which separates the d-dimensional data in to its best separable classes. However, in some cases, the training data is often not linearly separable. SVM introduces the notion of a "kernel induced feature space", which casts the data into a higher dimensional space where the data is separable. We used a freely available, highly accepted machine learning tool kit, WEKA [Bouckaert, 2010] in the implementation.

3 Experimental Results

3.1 Platform

Fig. 5 CRUISE: the experimental vehicle

The experimental test bed, CRUISE: CAS Research Ute for Intelligence, Safety and Exploration (Fig. 5), developed in-house was used for experimentation. CRUISE is equipped with range of sensors including GPS, cameras, LMS, accelerometers and an IMU. Number of computers mounted in the back tray, connected via Ethernet, are used for data collection and logging. A separate battery bank provides the required power.

As shown on right side of Fig. 5, a SICK LMS111 is mounted on the vehicle looking down for scanning the road surface. It is aligned with the central axis of the vehicle and scanning plane is perpendicular to the ground.

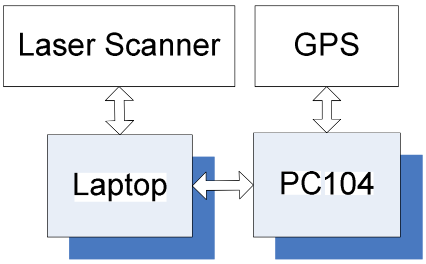


Fig. 6 The Hardware Structure of System

A laptop computer is used for laser data logging where as a PC104 computer logs the GPS data. Both computers are synchronized via Ethernet using NTP.

3.2 Data Collection

The experiment was performed in a fine day with average autumn temperature and humidity in an urban area of Sydney, Australia. CRUISE was driven on four types of roads, which were asphalt, concrete, grass, and gravel at different speeds while capturing data. Considering driving safety and practical constraints, the data was logged when the vehicle was driven on asphalt roads at speeds of 0-70 km/h, concrete roads at speeds of 30-40 km/h, grass roads at speeds of 10-20 km/h and gravel roads at speeds of 10-30 km/h, respectively. Critical vibration was felt by the passengers in the cab while running on grass roads over 20 km/h speeds, which was apparently not comfortable or safe for human and the vehicle with equipments. Data was collected along more than 30 km road segments. At least two people were required for the purpose, one was attending to data logging while the other was driving.

3.3 Experimental Results

The Speed Independency

The laser data collected were assumed to be minimally affected by the operating speed of the vehicle. This is reasonable as the LMS has a fast sampler which can capture range data in several microseconds.

This hypothesis was tested with data captured on Asphalt and Gravel roads at a range of different speeds. While the classifier was trained at a particular speed, it was tested at a different speed on the same road type. As shown in Table 1, the data set was divided into training and testing parts. It could be noted that the asphalt roads were the most widely available road type whereas concrete and grass roads were rare to find in Sydney.

Table 1 Off-line data organized for training and testing

Road Terrain Type	Training (m)		Testing (m)	
	Speed (km/h)	Distance (m)	Speed (km/h)	Distance (m)
Asphalt	20 ~ 40	1900	0 ~ 70	3948
Concrete	20 ~ 30	284	20 ~ 40	952
Grass	10	304	10 ~ 20	876
Gravel	20 ~ 30	1280	10 ~ 30	2712
Total		3768		8488

The Table 2 shows the classification results at different speeds. The first row shows the classification accuracies of Asphalt and Gravel tested at 40km/h (A40) and 10km/h (G10) while trained both at 20km/h (A20&G20) speed. Overall, the table shows very high accuracies leading to the conclusion that the LMS data is speed independent.

Table 2 Classification at different speeds

Training Speed (km/h)	**Testing Speed (km/h)**	***Asphalt Accuracy***	***Gravel Accuracy***
A20&G20	A40&G10	100.0%	99.2%
A20&G20	A30&G30	100.0%	100.0%
A20&G20	A30&G10	100.0%	99.2%
A30&G30	A20&G10	100.0%	100.0%
A30&G30	A40&G20	100.0%	100.0%

Classification Results based on Range Data

The training and testing data was all hand-labelled a priori. SVM classifier performed well on three road terrain types but not on the Asphalt road. As can be seen in Table 3, training with Asphalt and testing with all other road types has the worst accuracies. The Asphalt road has been heavily misclassified as Concrete road. This is mainly due to the significant ambiguities between Asphalt features and Concrete features. In fact, those spatial frequency features just demonstrate that the surface structure of Asphalt road and Concrete road are very similar.

Table 3 Range data only

Testing / Training	Asphalt	Concrete	Grass	Gravel
Asphalt	26.2%	39.3%	11.5%	23.0%
Concrete	0%	86.1%	13.9%	0%
Grass	0%	20.6%	76.7%	2.7%
Gravel	0%	2.3%	7.4%	90.3%
Average: 69.8%				

As for other three road terrain types, prediction accuracies of Concrete road, Grass road and Gravel road are 86.1%, 76.7% and 90.3% respectively. The structural differences obvious in gravel roads could be the reason for higher Gravel road classification accuracy. However, it could be noted that the overall average accuracy of road terrain type classification using LMS range data is just 69.8%.

The accelerometer data based classification reported in [Wang, 2012] has the problem of speed dependency. It required sufficiently large training data covering all speeds for better classification results. But if using LMS data, take this case for instance, it is not necessary to use all speed data in training phase but still provides a reasonable classification results.

Remission data

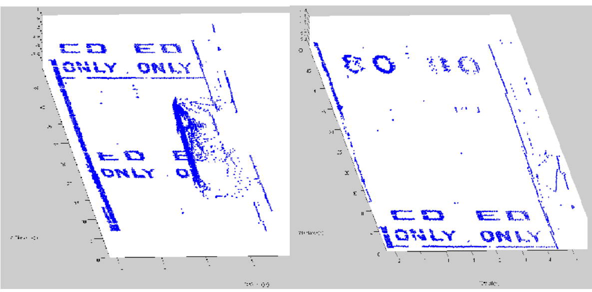


Fig. 7 Remission data

The reflection of a laser light is affected by object's surface properties and hence it is significantly affected by roadway scenes [Xiang, 2012]. The thresholded remission values of a certain data segment is shown in Fig. 7, where the blue points refer to reflective lane markings. In this particular scenario, the remission values can confuse the road type classifier. However in general, it performs well. That is because it can capture visual texture without being affected by environment lighting as does in camera images.

Classification based on Range and Remission data

The remission features were integrated to range features simply by combing Feature matrix (3) and feature matrix (4) to form a new feature matrix. All indices of samples were appropriately matched so that each range data sample corresponds to its remission data sample.

Table 4 Fusion of Range and Remission data

Testing / Training	Asphalt	Concrete	Grass	Gravel
Asphalt	99.9%	0%	0%	0.1%
Concrete	0%	91.6%	8.4%	0%
Grass	0%	6.4%	93.6%	0%
Gravel	1.0%	0%	0.5%	98.5%
Average: 95.9%				

The same classifier with same parameters as in the previous section was used here. As expected, the classification accuracies of each class has increased. As can be seen in Table 4, accuracy of the Asphalt road classification has dramatically increased from 26.2% to 99.9%. It can be explained that the remission features helps to provide a clearer difference between all of the classes than that of range value only. The average classification accuracy was also improved to 95.9% with both range and remission features.

4 Conclusion

In this paper, we have presented a method to classify road terrain types based on LMS data. Range data was used to estimate road surface features and the remission data was used to extract another set of features. Fusion of both types of features lead to higher classification accuracies. It was also shown that the accuracies were speed independent within the given operating ranges of speeds.

We are currently working on online implementation and prediction of future road terrain types based on multi-sensor fusion algorithms.

Acknowledgment

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ACRA 2012

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Contributors: Kodagoda, SHI, WANG

Key for the below column headings: show

Summary of reviews of pap120s1

Reviewer	Rel	Sound	Imp	Orig	Pres	Overall	Rec	Conf	Exp	BP
Reviewer 1	7	7	5	5	6	6	WEAK ACCEPT (3)	6	Some background (2)	NO (1)
Reviewer 2	7	5	4	3	6	5	WEAK ACCEPT (3)	6	Some background (2)	NO (1)
Reviewer 3	7	5	5	5	3	5	WEAK ACCEPT (3)	8	Knowledgeable (3)	NO (1)
Reviewer 4	7	7	4	3	6	6	WEAK ACCEPT (3)	7	Knowledgeable (3)	NO (1)
Averages:	7.0	6.0	4.5	4.0	5.2	5.5	3.0	6.8	2.5	1.0

Commitee Comments jump

Review of pap120s1 by Reviewer 1

to|

Comments for Authors:

The authors propose a technique for road terrain classification using rangefinder data. The algorithm extracts two features from the data - a spatial frequency feature and a remission-based feature. The authors show that by combining both features with an SVM classifier, the algorithm can distinguish between 4 common road types with a high degree of accuracy.

Spelling and grammatical error aside, the paper explains the algorithm quite clearly and it seems relatively easy to reimplement from reading the paper although the mechanism for training the SVM could be fleshed out a bit more.

A weakness of this paper is the lack of comparison with other methods. If I were to attempt to implement a road classification system on an autonomous vehicle, after reading this paper I would still not be sure whether it is worth employing the proposed algorithm because I have no point of reference to another state-of-the-art technique. Quantitively show me where does this algorithm outperform other methods using laser or vision and where it fails.

One area where autonomous vehicles have been deployed successfully is in mines and sparsely populated rural regions. Would dust significantly impede the algorithms performance?

It's unclear how robust this technique is to vibrations of the vehicle. An assumption is made that h_i, the height of the laser is fixed but this would change if the car vibrated. Is this a significant issue?

The author mentions that lane markings can confuse the remission feature. Would it be possible to just add a maximum threshold on the remission values to filter out highly reflective returns and maybe replace the values with the average value of surrounding pixels, if necessary.

One aspect of Table 3 that I feel warrants further explanation is the asymmetry between the asphalt and concrete. You mention in the text that the features look similar and hence the confusion of asphalt with concrete (39.3% false positives). However, why then does concrete not get confused with asphalt (0% false positives). It seems like there is an imbalance in the classifier that might be rectified with better training.

Minor changes: Sec2.2 H is the reference height however Figure 3 shows h_i. Should these match? Fig 1 is a little confusing. It is unclear that the laser scanner is rigidly attached to the vehicle. Maybe include a supporting frame in the image. Should the lowest block in Fig 2 be "Road Surface Estimate" rather than just the "Road Surface" which is not dependent on the blocks above it. Section 3 Is a bit short and under developed for a section of its own. It might make more sense to call Section 2 "Methodology" and change Section 3 to Section 2.4

Spelling: There are a number of words in the text that are unnecessarily capitalised Sec 1 Par 2 Road Terrain (small t) Sec2.1 arrangement of the Laser scanner (small l) known as Nearest-neighbour ... known as nearest-neighbour apriory .... apriori remission information of laser beam .... remission information of the laser beam causing somewhat speed dependency ... resulting in a dependence on speed. A looking down SICK ... a downward -looking SICK In a similiar way, x axis coordinate .... the x-axis coordinate Cas Research ... CAS research ? Sec. 4.2. "But if using laser scanner..." this sentence doesn't make sense. "As known" ... there is no need for this phrase. "without affected" ... without being affected it turned out classification rate ... it turned out the classification rate provide clearer difference of all classes .... provide a clearer difference between all of the classes

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Review of pap120s1 by Reviewer 2

top

Comments for Authors:

This paper details a road terrain type classification system using a SVM classifier which takes range data and remission values from a laser scanner as inputs. The authors acknowledged that there are many road terrain type classifiers in the literature based on a variety of sensors such as laser scanners, cameras, accelerometers, GPS and also wheel encoders. However, the authors only compared the performance of their system with respect to a range data only SVM classifier on 4 different terrain types making hard to gauge the actual improvement of the proposed system.

Detailed Comments/Questions:

1) Is "zi" in Equation 1 referring to "hi" in Figure 3?

2) How does the system deal with the variation of the laser scanner's pose to respect to the ground as the vehicle is travelling on uneven terrain which causes the the suspension system on the vehicle to compress and extend.

3) How accurate is the vehicle's estimated speed in Equation 2? How accurate does your GPS estimate the vehicle's actual speed when travelling at varying and constant speeds?

4) Authors may want to comment on the effect on the concatenated group of scans over 4 metres due to issues (2) and (3) and how this may or may not be an issue to the classifier.

5) Experimental results lack comparisons to state of the art systems. Authors should at least provide a qualitative comparison if quantitative comparisons are not feasible.

Typos/Grammatical Errors:

1) Rephrase Sect. 1 Para. 6 "...parametric uncertainties of the model causing somewhat speed dependency"

2) Rephrase Sect 2.1 Para. 1 " A looking down SICK LMS111..."

3) Sect 2.2 under "Speed Data Processing'' subsection "...unreasonable error scatted..."

4) Rephrase Sect. 3 Para 1 : "... turns out the best classification rate for road terrain type classification by numbers of off-line tests"

5) Confused with the sentence in Sect 4.3 under "Classification based on Range and Remission data" subsection "All incorrect predicted labels of Grass road shifted to the Asphalt road while part of Gravel road did as well"

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top

Comments for Authors:

The main contribution of the paper is the evaluation of a method using range and remission data from a lidar scanner to classify road surface type. The authors seem to have done some good work researching this topic; however, their presentation of results needs a little bit more work to be satisfactory.

The authors mention that classifiers in addition to SVMs were evaluated, but the paper has no such results; it would be good to present a table or plot comparing the performance of various classifiers.

Figure 3 and the corresponding equations (1) and (2) are very basic trigonometry and not really necessary to detail in the paper. It would be better for the authors to provide more details of the classification method, especially how the multi-class labeling is done since SVM are inherently binary classifiers.

The paper uses the units of Hz to describe the power spectral density features, however the data is a spatial signal and not a time signal. Therefore units of cycles per meter (1/m) would be more appropriate.

Table 1 is difficult to understand. The notation (i.e. 40%10) is not explained, and the accuracy percentages are relatively meaningless without any confidence bounds. It would be nicer to show type I and type II errors (false positives and false negatives) and indicate the statistical significance of the test.

Table 3 and 4 are a bit better, but I think that the terms "training" and "testing" here are confused with ground truth results and classifier outputs.

It would be good to show how the classifier performance varies with the size of the feature patch. How small can the patch be to still produce reasonable classification results? or is there a point where larger patches start to degrade the performance? This analysis would produce an interesting plot.

Figures 4 and 6 need a lot of work. The axis should be labeled with units and in a font size that is legible. The color range should be labeled with a colorbar, and all the plots should have the same color range. Better yet would be to color the surface plots by the remission values. Figure 6, doesn't make sense since the algorithm is not using thresholded remission values, and perhaps should be combined into figure 4.

I believe that the following reference has been missed and would be appropriate to include in the introduction: Comparison of boosting based terrain classification using proprioceptive and exteroceptive data A Krebs, C Pradalier, R Siegwart - Experimental Robotics, 2009 - Springer

I wonder why the authors employ gps for their speed sensor instead of the vehicles speedometer which can be queried via its OBD2 port and would be more reliable than GPS urban environments.

I also wonder if it matters to distinguish asphalt from concrete. Under what basis were the class distinctions chosen, and do they have a relevance to a particular application or are they just easy to hand label?

There are a number of typographical errors that a simple spell checker will not find such as: range vales -> range values rear to find -> rare to find a priory -> apriori It would be prudent to proof read the manuscript in more detail.

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to|

Comments for Authors:

The papers presents a method for road terrain type classification using laser scanner data on a vehicle. The subject is relevant, although there is significant related work. The approach appears sensible, however some points are not fully convincing, in particular the relative dependency to the vehicle's speed (affecting the scanning data sparsity), the influence of lane markings in remission data. The results are ok, although the variety of situations is limited. In particular, it seems that the training data and test data, albeit separate, are taken from the same series of experiments. One would like to see how the classification performs on new road that the vehicle has not trained on.

More specific comments follow:

Introduction: ---------- I question the comment that "Vehicle vibrations while driving on such surfaces could be thought as the most naïve data to be used for identifying different road terrain types". I am not sure what the authors meant by this, but there is a very good body of work on this subject, and proprioceptive data such as these vibrations are certainly relevant for this problem of terrain type classification.

"the stability of this method was affected by lack of camera’s exposure time": please rephrase this, as you seem to be talking about your implementation of such a camera-based method in prior work, not the work by Helmick et al.

I think the introduction should state more clearly what is the difference between the method presented in [Wang, 2012] and the one is this paper.

Section 2: Fig. 1 is showing the laser scanner and the car, but there is no apparent link between (virtual) laser scanner box and the car. Please show how the laser actually is mounted on the vehicle. The figure in this form is confusing.

2.2. "Establishment" does not seem to be the right word here.

Equation (1) and Fig. 3: hi is shown on the figure but not used in the text or anywhere (it should at least be defined somewhere). It's not exactly clear what is H and why it is needed. Is it assumed to be known and constant?

Explain why do you use a 1.3m wide region of interest. Is this the car width? I believe that it is not this value of 1.3m that leads to a 2cm sampling for each line scan. This should depend on the height of the laser scanner w.r.t. the road surface instead (which we don't know, please give the value).

What is the accuracy of your GPS localisation? This could be critical to the quality of your results.

The "on the other hand" at the bottom of page 2 is the wrong link.

Based on Fig.4, the authors claim "It is not difficult to establish a qualitative assessment of the plots for the differences purely by visual inspections". Apart from Gravel, I don't find this so obvious. Please justify.

You never indicate what is your (experimental) sampling in y. Obviously this depends on speed, but this raise the question: at what speed may your technique 'break' because of insufficient sampling in y? Would some regression be needed to "fill the gaps" and maintain a decent classification? I wonder how such classification can really be considered independent of speed, because of this sampling issue. At higher speeds, are you effectively scanning in "diagonals" on the road rather than on a horizontal line (perpendicular to the direction of travel)? what impact does it have on your classification, especially if your training data has been acquired at lower speeds, when this effect might be negligible?

Section 3: avoid using "turns out": it is informal and it sounds like you obtained some results "by accident".

Section 4: Fig. 5 deserves more legend. Is this the laser scanner you use that is shown on the right picture?

Any reason to use a laptop to collect laser scanner data rather than using the same PC 104 as for the GPS? How good was your synchronisation during your experiments? What do you mean by "Critical vibration was felt by the passengers in the cab "?

4.3: The authors say that laser data are assumed to be minimally affected by the speed of the vehicle because of the high scanning speed. I am not sure this hypothesis is valid at high speeds for a car, and this scanning speed should be given.

Table 1: I don't understand what the 20&20 mean. How much data have been used to generate those results? Note that the speeds presented here are different, but still pretty close (similar range).

"As shown in Table 2, the data set was divided into training and testing parts." : the table doesn't really show that. Table 2: note that speed 0 is impossible since you wouldn't have scanning in y as required.

"a priory" -> a priori

Smooth asphalt can be similar to concrete indeed. Why do you need to make the difference between the 2 anyway?

When you use remission data, it does seem that lane markings can have a strong impact indeed, providing information that may confuse your classifier. Was there any such lane marking in your training data? Could you account for this by recognising the remission is from lane markings and separate the corresponding data?

The formatting of the references needs to be fixed: - Please sort the references alphabetically. - Be consistent in the format (e.g. use always initials for first name, or always the full first name, always emphasize the book title etc.) - Do not capitalize some names in squared brackets, even if it is yours.

Committee Comments to Authors:

None

ACRA 2012:
http://www.araa.asn.au/acra/acra2012/

ARAA
AUSTRALIAN ROBOTICS
& AUTOMATION ASSOCIATION

About us

The Australian Robotics and Automation Association Inc. (formerly the Australian Robot Association Inc.) is a professional society in Australia and New Zealand that is concerned with robots, their applications and their implications, and related automation technologies.

The Association organises conferences and other meetings, and serves as a focal point for Australian industry and researchers concerned with robotics and automation.

Joining

Membership of the Association is available to interested organisations and individuals. Use our membership application form to join. ARAA's organisational members include leading robot suppliers, users and consultants.

Organisational Members of the ARAA

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ACRA

The association runs an annual conference Australasian Conference on Robotics and Automation (ACRA). The next conference will be held at the University of New South Wales between 2-4 December 2013. Details of ACRA2013 will appear here soon.

Field and Service Robotics (FSR) Conference

The association is a co-organiser of the FSR 2013 conference which will be held between 9-11 December 2013, at Queensland University of Technology in Brisbane. Details of FSR2013 can be found at the FSR website.

Mail list

Members of the ARAA get access to the ARAA mail list.

This list is for members to inform other members about activities in the field of robotics and automation in Australia and New Zealand. Mail on the list typically contains information on topics such as conferences, trade shows, job openings, student and post-doc positions, and significant news in the field.

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