Multimodal terrain analysis for an all-terrain crisis management robot

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Abstract

As the evolution in robotic technology is continuing, robots are more and more leaving the protected lab environment and entering the unstructured and complex outside world, e.g. for applications such as humanitarian demining or more generic crisis management tasks. Contrary to the indoor case, any robotic system which needs to navigate through an unstructured outdoor environment requires a means to judge whether the terrain in front of the robot is traversable or not. This so-called terrain traversability problem is no easy problem, as it depends on multiple factors. Some of these factors are external to the robotic system and very hard to measure or model, e.g. soil, vegetation, rocks, slopes, humidity, … Other factors are intrinsic to the robotic system used, e.g. the wheel diameter, motor torque, drivetrain system, …

It is clear that a generic terrain traversability estimation methodology, which would aim to model all of the aforementioned influences, would lead to an algorithm with an insurmountable number of difficult-to-tune parameters. Therefore, existing approaches towards terrain traversability estimation aim to simplify the problem. Two general approaches can be distinguished for doing this, each having their advantages and disadvantages. One type of techniques stems from the computer vision community and aims to classify the terrain based upon color image data from an on-board camera. A second series of approaches uses depth information, obtained either using a 3D Laser or a stereo camera, to infer traversability information.

In this paper, a novel stereo-based terrain-traversability estimation methodology is proposed. The novelty is that – in contrary to classic depth-based terrain classification algorithms – all the information of the stereo camera system is used, also the color information. Using this approach, depth and color information are fused in order to obtain a higher classification accuracy than is possible with uni-modal techniques.

Introduction

Autonomous robotic systems operating in unstructured outdoor environments need to estimate the traversability of the terrain in order to navigate safely. Traversability estimation is a challenging problem, as the traversability is a complex function of both the terrain characteristics, such as slopes, vegetation, rocks, etc and the robot mobility characteristics, i.e. locomotion method, wheels, etc. It is thus required to analyze in real-time the 3D characteristics of the terrain and pair this data to the robot capabilities.

Terrain traversability analysis is a research topic which has been in the focus of the mobile robotics community in the past decade, inspired by the development of autonomous planetary rovers and, more recently, the DARPA Grand Challenge. However, already in 1994, Langer et al. [5] computed elevation statistics of the terrain (height difference and slope) and classified terrain cells as traversable or untraversable by comparing these elevation statistics with threshold values. Most of the terrain traversability analysis algorithms employ such a cell-based traversability map, which can be thought of as a 2.5D occupancy grid. The problem with Langer's method was that the traversability was only expressed in binary forms and soon other researchers presented solutions to lift this limitation. In [7], Seraji proposed a fuzzy-logic traversability measure, called the Traversability index, which represents the degree of ease with which the regional terrain could be navigated. This degree was calculated on the basis of the terrain roughness, the slope and the discontinuity, as measured by a stereo vision system. Schäfer et al. presented in [6] a similar stereo-discontinuities based approach without explicit calculation of a traversability map. Other researchers [2] have

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embedded the stereo-based terrain traversability analysis in an on-line learning approach. The results of these methods depend greatly on the quality of the training set.

In [9], Ulrich and Nourbakhsch presented a solution for appearance-based obstacle detection using a single color camera. Their approach makes the assumption that the ground is flat and that the region in front of the robot is ground. In [3], Kim et al. present another single-camera traversability estimation method based upon self-supervised learning of superpixel regions. Besides monocular and stereo vision, laser range finders are a useful sensor for terrain traversability estimation. In [1], Andersen et al. present a method for terrain classification using single 2D scans. It can be argued that the basic problem with all these methodologies based on one sole sensing modality (be it vision-based or laser-based) is that the problem of traversability estimation is reduced to a lower dimension than it formally is, as the traversability of an area depends not only on its pure 3D characteristics (is it too high to climb or not?), but also on its object properties (is the object traversable or not?), which can be deduced from the objects' color.

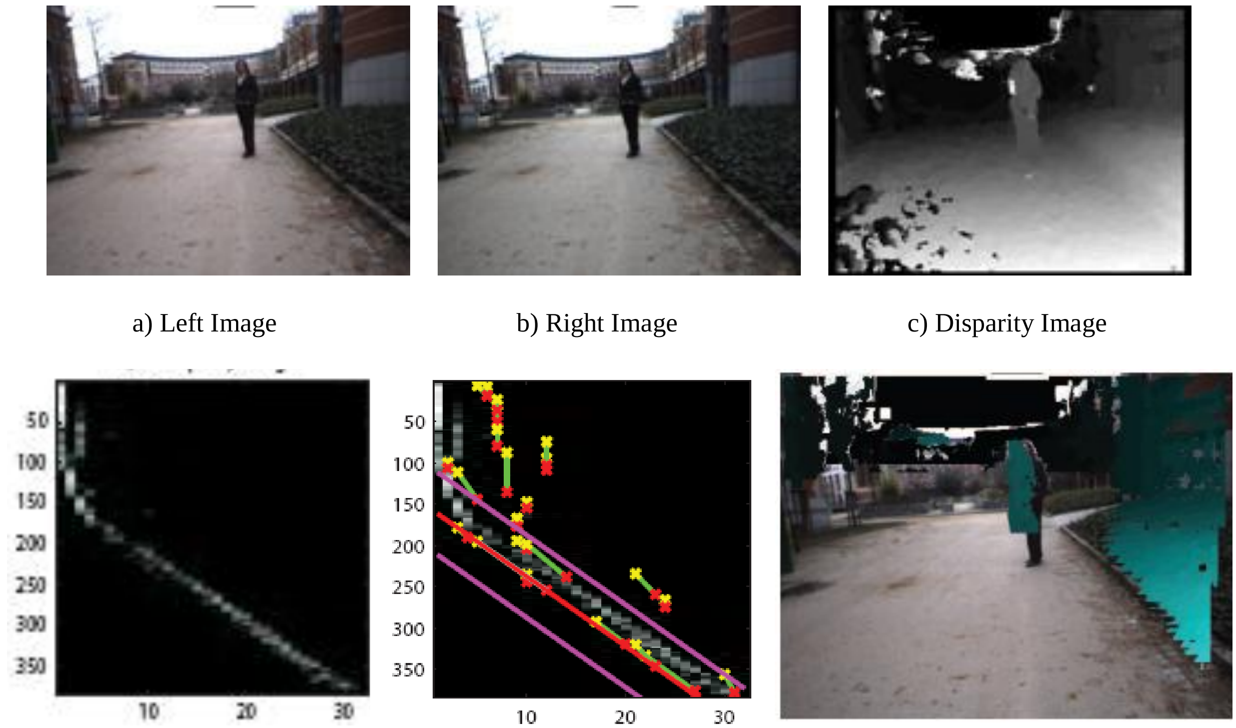
The Stanford Racing Team recognized this and proposed in [8] a methodology which fuses 3D laser and 2D color information. They utilized a Traversability Map based on data from six laser scanners registered with pose from an unscented Kalman Filter to classify grids as undrivable, drivable, or unknown. Unfortunately, pose error often led to a large error in the 3D data. To correct for this a Markov model was used to probabilistically test for the presence of an obstacle leading to an improved Traversability Map. In addition, parameters of the Markov model where tuned using a discriminative learning algorithm and data labeled through human driving. Data representing where the vehicle traveled was labeled as drivable while areas to the left and right of the vehicle were labeled as non-drivable. This significantly reduced the instances of false positives in the map. Finally, a mixture of Gaussians from RGB vision data was maintained for the drivable area of the Traversability Map. These Gaussians were used by an online learning algorithm to label data beyond the range of the laser map. Stanford's extension of the Traversability map represents perhaps the most sophisticated work in the area to date. However, it should be noted that the problem was formulated as a road following problem and has not been tested in off-road navigation scenarios. The problem with this approach, however, is that the required amount and cost of the sensing equipment and processing equipment in order to solve the terrain traversability estimation problem is that high that it is not suitable for practical robot systems. Therefore, we present in this paper an approach for outdoor terrain traversability which mixes 2D and 3D information for terrain classification, using only a simple stereo camera as input.

Methodology

Detecting obstacles from stereo vision images may seem simple, as the stereo vision system can provide rich depth information. However, from the depth image, it is not evident to distinguish the traversable from the non-traversable terrain, especially in outdoor conditions, where the terrain roughness and the robot mobility parameters must be taken into account. Our approach is based on the construction and subsequent processing of the *v-disparity* image [4], which provides a robust representation of the geometric content of road scenes. The v-disparity image is constructed by calculating a horizontal histogram of the disparity stereo image.

Consider 2 stereo frames, as shown in **Figure**1*a* and *b*, and the computed disparity image I_D, as shown in **Figure**1*c*. Then, the v-disparity image I_V can be constructed by accumulating the points with the same disparity that occur on a horizontal line in the image. **Figure**1*d* displays the v-disparity image I_V for the given input images. The classification of the terrain in traversable and non-traversable areas goes out from the assumption that the majority of the image pixels are related to traversable terrain of the ground plane. The projection of this ground plane in the v-disparity image is a straight line, from the top left to the bottom right of the v-disparity image. Any deviations from this projection of the ground plane are likely obstacles or other non-traversable terrain items.

As such, the processing of the v-disparity image comes down to estimating the equation of the line segment in the v-disparity image, corresponding to the ground plane. This is done by performing a Hough transform on the v-disparity image and searching for the longest line segment. Then, one must choose a single parameter which accounts for the maximum terrain roughness. As this parameter depends only on the robot characteristics, it only needs to be set once. This parameter sets the maximum offset in v-disparity space to be considered part of the ground plane. Any outliers are regarded as obstacles, which enables to compile an obstacle image I_O.



a) Left Image b) Right Image c) Disparity Image

d) V-Disparity Image e) Ground Plane in V-Disparity Image f) Obstacle Image

Figure 1: Stereo Processing

From this estimation, a number of pixels are selected which have a high probability of belonging to the ground plane (low distance to the estimated ground plane). The mean *a* and *b* color values in the *Lab* color space of these pixels are recorded as ***c***. The result of both data streams is then combined to optimize the classification result. For each pixel *i* in the image, the color difference $\left\|\mathbf{c}_i - \mathbf{c}\right\|$ and the obstacle density in the region where the pixel belongs to are calculated. The obstacle density δ_i is here defined as: $\delta_i = \frac{\langle o \in A_i \rangle}{\langle A_i \rangle}$, where *o* denotes the pixels marked as obstacles (high distance to the estimated ground plane) and A_i denotes the segment where pixel *i* belongs to. This allows us to define a traversability score as $\tau_i = \delta_i \left\|\mathbf{c}_i - \mathbf{c}\right\|$ which is used for classification. This is done by setting up a dynamic threshold, as a function of the distance measured. Indeed, as the error on the depth measurement increases with the distance, it is required to increase the tolerance on the terrain classification as a function of the distance.

Results

Figure 2 shows some frames of a test with the presented terrain traversability estimation algorithm. Obstacles are red, well traversable terrain is green. For this experiment, a Point Grey Bumblebee stereo camera was mounted on a heavy outdoor robot which was driving in an outdoor environment. It can be noticed that the classification is generally correct, as the obstacles (persons, body, and airplane) are well-detected.

Figure 1: Terrain Traversability Estimation Results (green = traversable; red=obstacle)

The terrain traversability estimation was integrated in the robot control architecture and used for robot navigation. As such, the robot was able to perform its task (executing a search pattern, searching for human victims after a plane crash) without human intervention.

Conclusions

In this article, we have presented a stereo-based terrain traversability estimation algorithm. This approach makes it possible to robustly classify the terrain of outdoors scenes in traversable and non-traversable regions quickly and reliably. Integrated in an autonomous robot control architecture, this enables a mobile agent to navigate autonomously in an unstructured outdoor environment.

References

[1] J. C. Andersen, M. R. Blas, O. Ravn, N. A. Andersen and M. Blanke: Traversable terrain classification for outdoor autonomous robots using single 2D laser scans. Journal of Integrated Computer-Aided Engineering, vol. 13(3), pp 223-232, 2006

[2] M. Happold, M. Ollis, N. Johnson, Enhancing supervised terrain classification with predictive unsupervised learning, in: Proc. of Robotics: Science and Systems, 2006

[3] D. Kim, S. Oh, and J. M. Rehg, "Traversability Classification for UGV Navigation: A Comparison of Patch and Superpixel Representations," *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 07)*, San Diego, CA, Oct 2007.

[4] R. Labayrade, D. Aubert, J. P. Tarel, "Real Time Obstacle Detection on Non Flat Road Geometry through V-Disparity Representation", IEEE Intelligent Vehicles Symposium, Versailles, June 2002.

[5] D. Langer. A Behavior-Based system for off-road navigation. IEEE Transactions on Robotics and Automation, vol 10, no 6, pp 776-783, 1994

[6] H. Schäfer, M. Proetzsch, K. Berns, Stereo-Vision-Based Obstacle Avoidance in Rough Outdoor Terrain International Symposium on Motor Control and Robotics – 2005

[7] H. Seraji. New traversability indices and traversability grid for integrated sensor/map-based navigation. Journal of Robotic Systems, vol 20, no 3, pp. 121-134, 2003

[8] S. Thrun, M. Montemerlo, H. Dahlkamp, D. Stavens, A. Aron, J. Diebel, P. Fong, J. Gale, M. Halpenny, G. Hoffmann, K. Lau, C. Oakley, M. Palatucci, V. Pratt, P. Stang, S. Strohband, C. Dupont, L. E. Jendrossek, C. Koelen, C. Markey, C. Rummel, J. van Niekerk, E. Jensen, P. Alessandrini, G. Bradski, B. Davies, S. Ettinger, A. Kaehler, A. Nefian, and P. Mahoney, "Stanley: The robot that won the darpa grand challenge: Research articles," *J. Robot. Syst.*, vol. 23, no. 9, pp. 661-692, 2006

[9] I. Ulrich and I. Nourbakhsh, "Appearance-Based Obstacle Detection with Monocular Color Vision," Proceedings of AAAI 2000, 2000.