Robotics and Autonomous Systems 61 (2013) 1051–1059

Contents lists available at ScienceDirect

Robotics and Autonomous Systems

journal homepage: www.elsevier.com/locate/robot

Probabilistic terrain classification in unstructured environments

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ARTICLE INFO

Article history:
Available online 11 August 2012

Keywords:
Markov random fields
Terrain classification
Sensor fusion

ABSTRACT

Autonomous navigation in unstructured environments is a complex task and an active area of research in mobile robotics. Unlike urban areas with lanes, road signs, and maps, the environment around our robot is unknown and unstructured. Such an environment requires careful examination as it is random, continuous, and the number of perceptions and possible actions are infinite.

We describe a terrain classification approach for our autonomous robot based on Markov Random Fields (MRFs) on fused 3D laser and camera image data. Our primary data structure is a 2D grid whose cells carry information extracted from sensor readings. All cells within the grid are classified and their surface is analyzed in regard to negotiability for wheeled robots.

Knowledge of our robot's egomotion allows fusion of previous classification results with current sensor data in order to fill data gaps and regions outside the visibility of the sensors. We estimate egomotion by integrating information of an IMU, GPS measurements, and wheel odometry in an extended Kalman filter.

In our experiments we achieve a recall ratio of about 90% for detecting streets and obstacles. We show that our approach is fast enough to be used on autonomous mobile robots in real time.
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1. Introduction

Autonomous navigation in unstructured environments is a current and challenging task in robotics. Mobile systems need a detailed interpretation of the surrounding terrain to avoid obstacles and to regard the negotiability of the surface. Modern 3D laser range finders (LRFs) provide a rich and thorough picture of the environment in the form of 3D distance measurements. The vast amount of data acquired by 3D LRF makes it infeasible to use directly for a path planning algorithm. Therefore, as a first step, a reduction of the large point cloud is necessary and an efficient data structure is essential. Our work was motivated by the terrain analysis performed by Neuhaus et al. [1], where a two dimensional grid structure was introduced to provide fast access to negotiability estimates.

Differentiation between different surfaces from laser range measurements alone is a difficult task. A second type of sensor can provide more information for surface structures. By calibrating three cameras to our LRF we are able to access the fused data in one coordinate system. This allows us to determine color and texture information of the 3D points in the field of view of each camera. In unstructured environments, classification of the terrain can be challenging due to sensor noise, varying density of the data, egomotion or percussions on rough terrain. For that reason we apply a Markov random field (MRF) to add context-sensitive information to the terrain classification, which models the relationships in our data structure.

In order to interpolate data gaps and regions with sparse sensor data, our MRF accesses previous classification results. An extended Kalman filter (EKF) works on fused inertial measurement unit (IMU), Global Positioning System (GPS), and wheel odometry data to estimate the egomotion of our robot. The result is refined using the 2D Iterative Closest Point (ICP) algorithm based on virtual 2D scans extracted from the data of our 3D LRF.

Our goal is to determine the negotiability of the surrounding terrain with a MRF in real time based on the sensors described Section 2. Therefore, we discuss related work in Section 3 before describing our terrain classification approach with MRFs in detail in Section 4. Experiments and results are depicted in Section 5. A conclusion is given in Section 6.

2. Hardware

As shown in Fig. 1 we use a Velodyne HDL-64E S2 [2] and two different camera types. The head of the Velodyne consists of 64 lasers which permanently gather data of the environment as

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doi:10.1016/j.robot.2012.08.002

Fig. 1. Deployed sensors and robot: A 3D laser range finder and two different commercially available cameras are used to perceive the environment. Sensors are mounted on top of a 500 kg outdoor robot.

the head spins at a frequency of up to 15 Hz around the upright axis. The sensor thereby produces a rich dataset of 1.8 million distance measurements per second. The data points of one full rotation are accumulated into one point cloud. A Logitech HD Pro Webcam C910 [3] is installed to the front and two Philips SPC1300NC [4] cameras are fixed on the left and the right side of the construction. The sensors are either mounted on top of a 500 kg robot (autonomous driving), the Mustang MK I (cf. Fig. 1), or on a car (recording of sensor data). We further use a Navilock NL-302U GPS receiver, an xSens MTi IMU, and a Speed Wedge SW01 radar-based speed sensor.

3. Related work

This work was motivated by results from image processing, terrain classification, and probabilistic robotics. The following presentation of the state of the art is therefore separated into image processing (Section 3.1), terrain classification (Section 3.2), and egomotion (Section 3.3).

3.1. Image processing

Image segmentation is a fundamental task in many computer vision applications. MRFs have been frequently used in this field, especially for segmentation tasks.

Szirányi et al. [5] address the problem of the huge amount of computing power required for Markovian approaches. They introduce a fully-parallel architecture for MRF segmentation of images and show that the Markovian labeling approach can be implemented in fully parallel cellular network architectures.

Meas-Yedid et al. [6] use a MRF clustering approach for color segmentation based upon color and spatial information. Their approach proves robust against noise, marker color changes, illumination changes, and blurring during the performed experiments.

A MRF image segmentation model that combines color and texture features is presented by Kato and Pong [7]. Segmentation is obtained by classifying pixels into different pixel classes, which are represented by multi-variate Gaussian distributions either computed of training data or estimated from the input image.

Qazi et al. [8] present a segmentation methodology with robust parametric approximations proposed for multichannel linear prediction error distribution. They use a region-size-based energy term with the conventional Potts energy model and present improved results in terms of percentage errors of color texture segmentation in the case of high-resolution multispectral satellite images.

D'Angelo et al. [9] provide a MRF description of an unsupervised color image segmentation algorithm. Their system is based on a color quantization of the image in the Lab color space and uses a fuzzy *k*-nearest neighbors algorithm.

Besides color images, RGB-D sensors like the Microsoft Kinect emerged and granted the opportunity of color, texture and depth data in one dataset. Herbst et al. [10] use an RGB-D camera and apply a multi-scene MRF model to detect objects that moved between multiple visits to the same scene. By combining shape, visibility and color cues, their approach is able to detect objects even without texture within the scenes.

A MRF that integrated high-res image data into low-res range data was presented by Diebel and Thrun [11]. Their MRF exploits the fact that discontinuities in range and coloring tend to co-align and recovers the range data at the same resolution as the image data.

3.2. Terrain Classification

There exist various approaches to classify the terrain surrounding an autonomous mobile robot platform. Especially image- or laser-based strategies are wide spread when terrain negotiability information is needed.

Image-based strategies either use a single, stereo or combined setup of digital and infrared cameras. Konolige et al. [12] and Alberts et al. [13] both use stereo vision approaches to maneuver a vehicle through unstructured environments. Stereo vision allows them an extraction of traversable regions from the camera video streams. Furthermore, Vernaza et al. [14] present a camera-based terrain classification approach for the DARPA LAGR program. Their approach uses a MRF that classifies image data of a stereo system into obstacles or ground regions for an autonomous robot.

Negative obstacles (non-negotiable regions underneath the ground level) present a difficult challenge in non-urban environments. Thermal infrared images have the characteristic that negative obstacles remain warmer than the surrounding terrain in the night. Rankin et al. [15] therefore combine thermal signatures and stereo range data to determine the terrain negotiability.

Laser-based approaches either work with a 2D, 2D sensors on stepper motors or a 3D LRF. Wurm et al. [16] use the laser remission value of a 2D LRF on a pan-tilt unit to classify the surface terrain based on the resulting 3D scans. In this way, they can detect grass-like vegetation and prefer paved routes with their robot.

Another approach for terrain classification is presented by Wolf et al. [17]. Their robot uses a 2D LRF oriented to the ground, records data while driving and produces 3D maps using Hidden Markov models. The authors are able to differentiate flat areas from grass, gravel or other obstacles.

Vandapel et al. [18] segment 3D distance measurements and classify the segments into three different classes for terrain surface, clutter or wires. Their approach worked with a detailed stationary 3D sensor as well as on a mobile platform with a rotating 2D scanning mount.

Ye and Borenstein [19,20] present an algorithm for terrain mapping with a 2D LRF. Their LRF is mounted at a fixed angle to the ground in front of their robot and creates an elevation map while driving.

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