



Self-learning classification of radar features for scene understanding

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ARTICLE INFO

Article history:

Available online 4 April 2012

Keywords:

Field robotics
Radar-based perception
Self-learning classifier

ABSTRACT

Autonomous driving is a challenging problem in mobile robotics, particularly when the domain is unstructured, as in an outdoor setting. In addition, field scenarios are often characterized by low visibility as well, due to changes in lighting conditions, weather phenomena including fog, rain, snow and hail, or the presence of dust clouds and smoke. Thus, advanced perception systems are primarily required for an off-road robot to sense and understand its environment recognizing artificial and natural structures, topology, vegetation and paths, while ensuring, at the same time, robustness under compromised visibility. In this paper the use of millimeter-wave radar is proposed as a possible solution for all-weather off-road perception. A self-learning approach is developed to train a classifier for radar image interpretation and autonomous navigation. The proposed classifier features two main stages: an adaptive training stage and a classification stage. During the training stage, the system automatically learns to associate the appearance of radar data with class labels. Then, it makes predictions based on past observations. The training set is continuously updated online using the latest radar readings, thus making it feasible to use the system for long range and long duration navigation, over changing environments. Experimental results, obtained with an unmanned ground vehicle operating in a rural environment, are presented to validate this approach. A quantitative comparison with laser data is also included showing good range accuracy and mapping ability as well. Finally, conclusions are drawn on the utility of millimeter-wave radar as a robotic sensor for persistent and accurate perception in natural scenarios.

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1. Introduction

Research in mobile robotics aims to develop technologies that allow vehicles to travel longer distances with limited human supervision. If robotic vehicles could reliably and robustly drive through unknown terrain toward a given location, the implications would be of great importance for many applications including exploration and reconnaissance (both on Earth and extra-terrestrially), search and rescue operations, and driving safety (e.g., development of automatic obstacle avoidance systems). Some notable examples can be found in the literature. On Mars, two robotic rovers have been exploring and collecting data since 2004. The Mars Rovers, however, are carefully monitored and controlled; they cannot be considered as fully autonomous [1]. Another prominent example is the 2005 DARPA Grand Challenge [2], which featured fully autonomous vehicles racing over a 212-km desert course. Nevertheless, the Grand Challenge required vehicles to drive autonomously from waypoint to waypoint along a desert

road: an arguably easier task than off-road navigation through arbitrary terrain. Although autonomous navigation has inspired decades of research, it still remains an open and active field of investigation. One of the critical challenges is accurate and robust scene understanding to perform many important tasks, including environment segmentation and classification, mapping and identification of terrain regions that can be safely traversed. One additional problem connected with autonomy in field scenarios is that visibility conditions are often poor. Day/night cycles change illumination conditions. Weather phenomena such as fog, rain, snow and hail impede visual perception. Dust clouds rise in excavation sites, and agricultural fields, and they are expected during planetary exploration. Smoke also compromises visibility in fire emergencies and disaster sites. Laser and vision are common imaging techniques affected by these conditions [3]. Sonar is not affected by visibility restrictions. However, it is considered of limited utility for field robots due to high atmospheric attenuation, noise, and reflections by specular surfaces. While laser scanners and cameras may have difficulties sensing in dusty environments, radar operates at a wavelength that penetrates dust and other visual obscurants and it can be successfully used as a complementary sensor to conventional range devices. Furthermore, radar can provide information

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of distributed and multiple targets that appear in a single observation, whereas other range sensors are generally limited to one target return per emission, although multi-peak and last-peak-based lasers solve this problem to some extent, and are becoming more common. Nevertheless, radar has shortcomings as well, such as large footprint, specular effects, and limited range resolution, all of which may result in poor environmental survey or difficulty in interpretation. In this research, we propose the use of millimeter-wave (MMW) radar for accurate and persistent perception of the environment. Scene understanding has been one of the goals of imaging sensor systems in general and particularly of computer vision for decades. Recently, the application of statistical learning has given rise to new interest in this field [4]. Statistically trained models have an advantage over deterministic, hand-tuned systems, especially when the complexity of the model exceeds the capabilities of human experts, as is the case with robust scene analysis. This paper presents an adaptive self-learning classifier using radar data. First, the system automatically learns to associate the appearance of radar data with class labels during a training stage. Then, it makes predictions based on past observations classifying new data into two broad categories, namely ground and non-ground. The ground class corresponds to returns from the terrain, whereas the non-ground class corresponds to all other returns, including sensor misreading and reflections from above-ground objects (i.e., obstacles) or from occluded areas. Since the characteristics of the ground may change geographically and over time, the system is continuously retrained in every scan: new automatically labeled data are added to the ground model replacing the oldest labels in order to incorporate changes in the ground appearance.

The radar-based classifier leads to the following main advantages: (a) enabling technology for all visibility-condition navigation systems, (b) self-learning training of the classifier, where the radar allows the vehicle to automatically acquire a set of ground samples, eliminating the need for time-consuming manual labeling, (c) continuous updating of the system during the vehicle's operation, thus making it adaptive and feasible for long range and long duration navigation applications, and (d) accuracy improvement in range estimation for enhanced environment mapping.

In this investigation, a mechanically scanned MMW radar, designed for perception and navigation in low visibility conditions, is employed. Although the sensor is custom built at the Australian Centre for Field Robotics (ACFR), it is similar in performance to other commercially available systems.¹ It is a 95-GHz frequency-modulated continuous wave (FMCW) MMW radar that reports the amplitude of echoes at ranges between 1 and 120 m. The wavelength is $\lambda = 3$ mm, and the 3-dB beamwidth is about 3.0 deg in elevation and azimuth. The antenna scans across the angular range of 360 deg at a scan frequency of about 3 Hz. The range raw resolution is about 0.32 m at 20 m [5]. The radar is integrated with the CAS Outdoor Research Demonstrator (CORD): an eight-wheel, skid-steering all-terrain unmanned ground vehicle (UGV) (see Fig. 1), which has been employed for the testing and the field validation of the system. The robot's sensor suite is completed by four 2D SICK laser range scanners, a mono-charge-coupled device (CCD) color camera, a thermal infrared camera, and a real-time kinematic/differential global positioning system/inertial navigation system (RTK DGPS/INS) unit that provides accurate pose estimation of the vehicle.

The remainder of the paper is organized as follows. Section 2 reports related research in the field, whereas basic principles of radar sensing are recalled in Section 3. The proposed radar-based classifier is described in detail in Section 4. In Section 5, the system is validated in field tests performed with the CORD UGV. Section 6 concludes this paper.



Fig. 1. The CORD UGV employed in this research. The sensor suite is visible, attached to a rigid frame.

2. Previous work

Considerable progress has been made in recent years in designing autonomous, navigation systems for unstructured environments [6]. Progress has also been made in high-level scene analysis systems [7,8]. In this section, research is organized by its learning strategy: deterministic (no learning), supervised, and self-supervised. Estimating the traversability of the surrounding terrain constitutes an important part of the navigation problem, and deterministic solutions have been proposed by many, [9–11], where some features of the terrain including slope, roughness, or discontinuities are analyzed to segment the traversable regions from the obstacles. In addition, some visual cues such as color, shape and height above the ground have also been employed for segmentation in [12,13]. However, these techniques assume that the characteristics of obstacles and traversable regions are fixed, and therefore they cannot easily adapt to changing environments. Without learning, such systems are constrained to a limited range of predefined environments. A number of systems that incorporate supervised learning methods have also been proposed, many of them in the automotive field and for structured environments (road-following). These include ALVINN (Autonomous Land Vehicle in a Neural Network) by Pomerleau [14], MANIAC (Multiple ALVINN Network In Autonomous Control) by Jochem et al. [13], and the system proposed by LeCun et al. [15]. ALVINN trained a neural network to follow roads and was successfully deployed at highway speed in light traffic. MANIAC was also a neural net-based road-following navigation system. LeCun used end-to-end learning to map visual input to steering angles, producing a system that could avoid obstacles in off-road settings, but did not have the capability to navigate to a goal or map its surroundings. Many other systems have been proposed in recent years that include supervised classification [16,17]. These systems were trained offline using hand-labeled data, thus limiting the scope of their expertise to environments seen during training. Dima et al. [18] recognized this problem and proposed using active learning to limit the amount of labeled data in a mobile robot navigation system. Only recently, self-supervised systems have been developed that reduce or eliminate the need for hand-labeled training data, thus gaining flexibility in unknown environments. With self-supervision, a reliable module that determines traversability can provide labels for inputs to another classifier. Using this paradigm, a classifier can be trained online using data from the reliable sensor (such as laser or vision). An example can be found in Milella et al. [19], where a visual classifier was trained by radar-driven labels. Brooks and

¹ For example, <http://www.nav-tech.com/Industrial%20Sensors2.htm>.

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