Chapter 4.18

Machine Learning for Visual Navigation of Unmanned Ground Vehicles

Artem A. Lenskiy
University of Ulsan, South Korea

Jong-Soo Lee
University of Ulsan, South Korea

ABSTRACT

The use of visual information for the navigation of unmanned ground vehicles in a cross-country environment recently received great attention. However, until now, the use of textural information has been somewhat less effective than color or laser range information. This chapter reviews the recent achievements in cross-country scene segmentation and addresses their shortcomings. It then describes a problem related to classification of high dimensional texture features. Finally, it compares three machine learning algorithms aimed at resolving this problem. The experimental results for each machine learning algorithm with the discussion of comparisons are given at the end of the chapter.

DOI: 10.4018/978-1-60960-818-7.ch4.18

INTRODUCTION

Literature Overview

The area of autonomous driving on- and off-road vehicles is expanding very rapidly. A great deal of work has been done developing autonomous navigational systems for driving along highways and roads in an urban environment. The autonomous navigation in determined and rigid urban environment with lanes, road markers and boards is relatively easier than the off-road autonomous navigation. In off-road navigation the significantly changing environment with fuzzy or no roads creates a new complexity for navigational issues. Only recently has cross-country navigation received appropriate attention. A good example is The Grand Challenge which was launched by the Defense Advanced Research Projects Agency

(DARPA) in 2003. The original goal of the project was to stimulate innovation in unmanned ground vehicle navigation. Two years later an unmanned ground vehicle (UGV) named Stanley was able to navigate a 132-mile long off-road course and complete it in 6 hours 53 minutes (Thrun, et al., 2006).

UGVs are usually equipped with multiple sensors to operate in a variety of cross-country environments (Figure 1). This equipment along with sophisticated algorithms serves to solve navigational problems such as map building, path planning, land mark detection, position estimation and obstacle avoidance. In this chapter we focus on the visual terrain segmentation task. The terrain segmentation allows the robot to detect obstacles and select the optimal path. Based on the information obtained by means of terrain segmentation, the robot is able to avoid unnecessary stops caused by traversable tall patches of grass. The segmentation information also allows adjusting traversal velocity depending on the terrain slippery factors.

There are multiple ways to segment a cross-country scene image, depending on what image characteristics are taken into account. Regardless of what characteristics are used, the final goal is to separate spatial image regions on the basis of their similarity. In the terrain segmentation task, image characteristics as color(Manduchi, 2006; Rasmussen, 2002), texture(Castano, Manduchi, & Fox, 2001; Sung, Kwak, & Lyou, 2010) and range data(Dahlkamp, Kaehler, Stavens, Thrun, & Bradski, 2006; Lalonde, Vandapel, Huber, & Hebert, 2006) are commonly utilized. The best terrain segmentation results are obtained when all characteristics are incorporated in the segmentation process. Nevertheless, in this chapter texture information is applied for cross-country scene segmentation. Depending on the terrain type, some image characteristics are more distinctive than others. Particularly, color information is useful in distinguishing classes such as sky, dry or green vegetation. However, there are a number of shortcomings associated with color segmentation algorithms. Compared to texture, color based segmentation algorithms are less robust to brightness changes caused fluctuations in natural illumination or shadows. Another demerit is that red, green, and blue color components that constitute color space are less discriminative than multidimensional texture features. Finally, color segmentation does not work at night, while texture segmentation can be applied to IR images captured at night. Nevertheless, adaptive color segmentation algorithms are useful especially in combination with other types of features. The off-road scene segmentation algorithm implemented in Stanley (Dahlkamp, et al., 2006; Thrun, et al., 2006) (the DARPA Grand Challenge winner) did not take into account texture information. There are likely two reasons for this. Texture features are usually computationally expensive to extract, and until now the performance of texture features was quite unsatisfactory compared to other scene characteristics.

Figure 1. An unmanned ground vehicle

Rasmussen (Rasmussen, 2002), provided a comparison of color, texture, distance features measured by the laser range scanner, and their combination for the purpose of cross-country scene segmentation. The segmentation was the worst when texture features were used alone. In the case when 25% of all features were used for training, only 52.3% of the whole feature set was correctly classified. There are two probable explanations of this poor result. One is related to the feature extraction approach. The feature vector consisted of 48 values representing responses of

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