Obstacle Detection Algorithms of Autonomous Vehicles

Michael Bao[1] and Andrea Angquist[2]

Henry M. Gunn High School[1], Pivotal Labs[2]

INTRODUCTION

Research Question

What kinds of obstacle detection algorithms do autonomous vehicles use and how do they work?

Introduction and Background

An autonomous vehicle is defined as a vehicle that is capable of sensing its environment and safely navigating without human input (Gehrig and Stein 1508). In order for a vehicle to truly be autonomous, it must recognize and detect its surroundings, react accordingly to the actions of other cars and obstacles, follow traffic rules, and drive flawlessly (Wagner and Koopman 2). One crucial aspect of the algorithms for an autonomous vehicle is obstacle detection because its perception and visualization of the surroundings dictate its subsequent set of actions. In the present, many obstacle detection algorithms have been developed with differences in functionality and behavior. And these obstacle detection algorithms have many flaws and do not take certain factors and unique situations into account. Currently, obstacle detection algorithms of autonomous vehicles are able to locate and track moving and stationary objects but struggle with telling objects apart, distinguishing between dangerous and harmless situations. and ascertaining the purposes and intentions of other objects, signs, cars, cyclists, and people (Urmson et al. 427). This research question aims to explore and determine some of the obstacle detection algorithms that autonomous vehicles use. Gaining a clearer and better understanding of these obstacle detection algorithms will facilitate the discovery and understanding of their current flaws.

RESEARCH METHODOLOGIES

My research will be conducted by collecting information from scientific and academic journals and papers. When collecting data from these sources, I am looking for explanations and descriptions of the concepts involved with the obstacle detection algorithms, specifically: the methods for identifying and recognizing obstacles, keeping track of their motion and location, and processing and applying their visual input. Pure research will be carried out because I will study and analyze the researched obstacle detection algorithms to further my learning and knowledge. I will collect qualitative data because it consists of the theoretical and conceptual models of how the algorithms function; it will not involve quantities or numerical values.The general population used in this study is the different kinds obstacle detection algorithms used by different autonomous vehicles. For my sample, I will select the most detailed and thorough obstacle detection algorithm papers that provide the most information. The data will be organized by each type of autonomous vehicle (ground, air, underwater), and laid out in outline form for simplicity and easy understanding. The analysis consists of finding differences, similarities, and current flaws of the algorithms, allowing me to determine which algorithm is the most effective and adaptive and to postulate modifications that will improve upon the current algorithm designs.

RESULTS

Underwater Autonomous Vehicle Obstacle Detection Algorithms

Underwater Vehicle Obstacle Detection Using a Multi-beam Forward looking Sonar (Fig. 1)

1) Segmentation: identify the regions of the image containing obstacles.
2) Feature Extraction: potential obstacles and their features (position, moments, area) are computed. These features will be used later to discard false alarms and track the obstacles and the vehicle.
3) Tracking: provide a dynamic model of the obstacles. Considering the amount of data to be processed, the tracking drives the segmentation and reduces the computational cost.

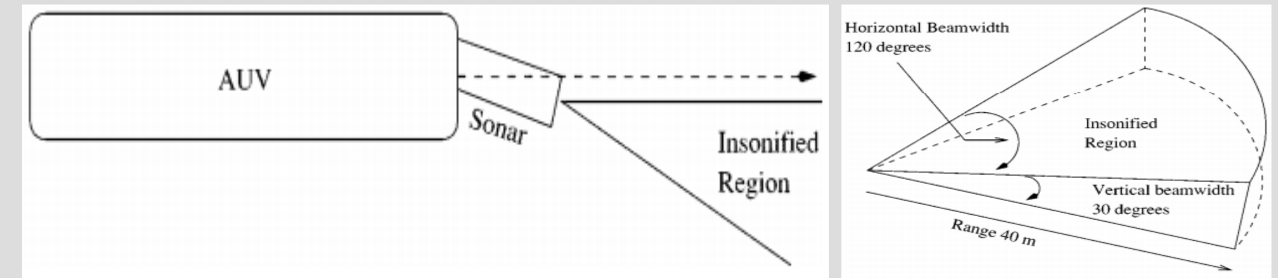

Figure 1: sonar characteristics and mounting configuration.

Obstacle Detection for the MEREDITH Autonomous Underwater Vehicle (Fig. 2), which is a built autonomous underwater vehicle.

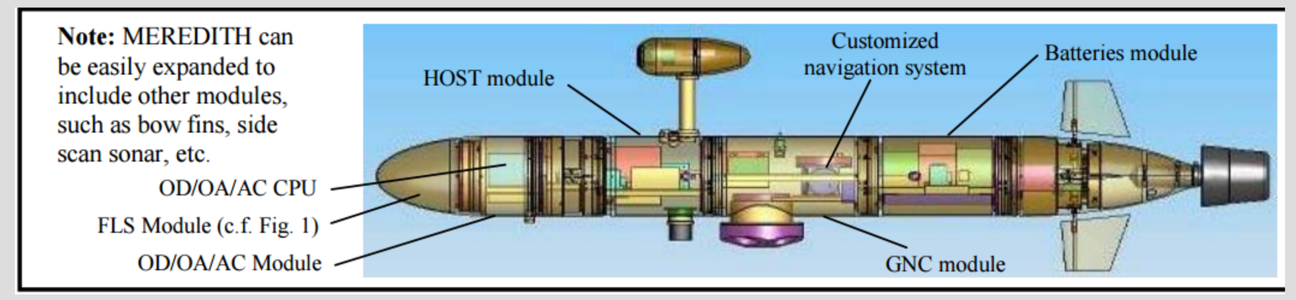

Figure 2: MEREDITH structure

The algorithm performs spatial and temporal filtering to the sonar data which are synchronized or time-tagged with the vehicle navigation inputs, which include body and earth positions, velocities, and orientation. The spatial filtering consists of an image processing algorithm which aims to extract obstacles from each sonar frame in sync with its computed 2D positions. The image processing techniques consist of the following:

1. Median filtering: reduces noise and removes outliers. The window size used for the filter is 3 by 3 and the boundary behavior used is symmetrical for better border behavior.
2. Morphology: locates objects and boundaries from the filtered image. This includes erosion, dilation and edge detection.
3. Adaptive Thresholding: segmentize the hotspots and the background to generate a binary image in every frame.

Aerial Autonomous Vehicle Obstacle Detection Algorithms

Obstacle Detection for Autonomous Aircraft Using Sky Segmentation

a. The algorithm identifies obstacles by segmenting the image into sky and non-sky regions, which is a horizon. The non-sky regions are then treated as obstacles.
b. Once the horizon is found, all non-sky pixels above the horizon can be treated as obstacles in the path of the aircraft and those below can be ignored (Fig. 3).

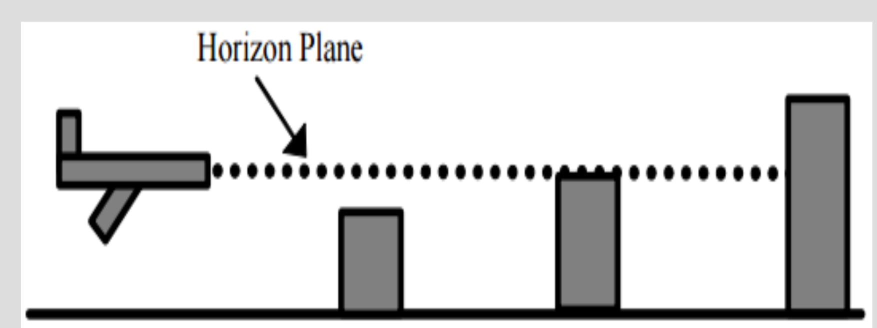

Figure 3: Location of obstacles with respect to horizon

Ground Autonomous Vehicle Obstacle Detection Algorithms

Obstacle Detection and Terrain Classification for Autonomous Off-Road Navigation

a. The algorithm relies on a color-based classification system to label the detected obstacles according to a set of terrain classes. It also uses laser rangefinder (ladar) data, which allows one to discriminate between grass and obstacles (such as tree trunks or rocks), even when such obstacles are partially hidden in the grass (Fig. 4).
b. The algorithm analyzes the slant of surface patches in front of the vehicle and identifies patches that are steep enough to represent a hurdle for the vehicle. The analysis is carried out on the range data produced by a laser rangefinder.

Stereo Vision-based Vehicle Detection

a. The algorithm is based on the following considerations: a vehicle is generally symmetric, characterized by a rectangular bounding box which satisfies specific aspect ratio constraints, and placed in a specific region of the image (Fig. 5).

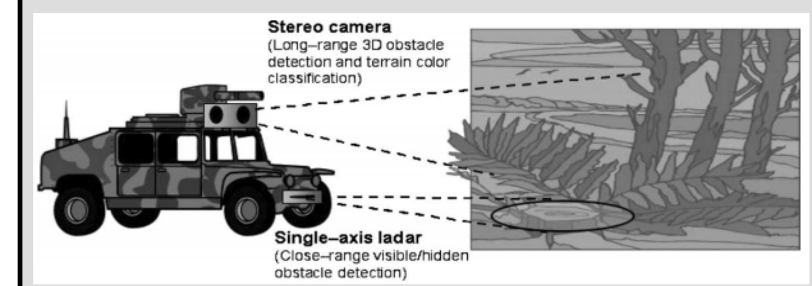

Figure 4: obstacle detection sensor system

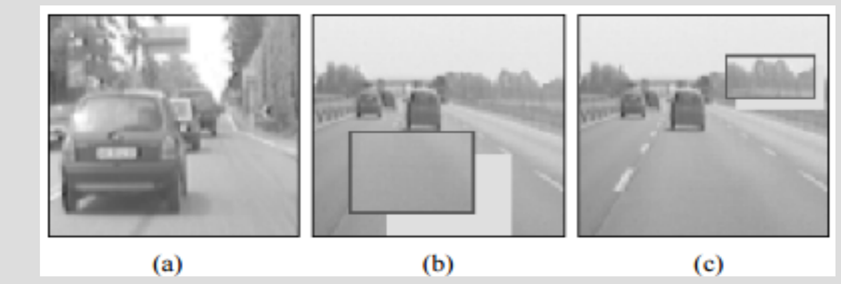

Figure 5: (a) a strong sun reflection reduces the vehicle gray level symmetry; (b) a uniform area can be regarded as a highly symmetrical region; (c) background symmetrical patterns.

These features are used to identify vehicles in the image in the following steps:

1. An area of interest is identified on the basis of road position and perspective constraints. This area is searched for possible vertical symmetries; not only gray level symmetries are considered, but vertical and horizontal edges symmetries as well (Fig. 5).
2. Once the symmetry position and width have been detected, a new search begins, aimed at the detection of the two bottom corners of a rectangular bounding box.
3. Finally, the top horizontal limit of the vehicle is searched for, and the preceding vehicle localized.

ANALYSIS/CONCLUSION

Based on the researched obstacle detection algorithms, some common similarities and differences came up between the three categories of autonomous vehicles and within each category as well. For underwater autonomous vehicles (UAVs), all three algorithms use sonar sensors to collect visual data about the obstacles. A difference between the three UAVs is how they incorporate and process the sonar data to build a representation of the obstacles around them. For aerial autonomous vehicles (AAVs), both algorithms factor in the velocity of the AAV and the velocities of surrounding obstacles to determine the subsequent positions of the obstacles in relation to the AAV. One algorithm uses sky segmentation, where obstacles are detected by segmenting the image into sky and non-sky regions and treating the non-sky regions as obstacles, while the other uses. The other algorithm is a bin-occupancy filter that tracks multiple targets and investigates if there is a target at a given point in space; it uses a model of the surveillance region which employs small "bins", which a target may or may not occupy. For ground autonomous vehicles (GAVs), all algorithms utilize stereo processing and visualization. In addition, all algorithms make comparisons between images at different second intervals, allowing the autonomous vehicle to detect sudden changes in the image compositions, signifying that an obstacle is present. The methods used for image comparison and processing and the equipment used differ across the algorithms for GAVs.

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