ROSE-HULMAN INSTITUTE OF TECHNOLOGY

LITERATURE REVIEW

CSSE463: IGVC VISION

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Summary

This paper describes a driverless navigation system based on custom hardware built to infer road conditions from stereoscopic imaging. Called the "Generic Obstacle and Lane Detection" system (GOLD), the mobile lab used real-time photos gathered to find lane lines, including the center, along with any imposing obstacles, which could be used to improve road safety. After removing the effect of perspective to reorient the road view, lane lines were detected in a manner similar to edge detection, finding pixels which were whiter and brighter than surrounding areas. In order to fill in gaps where pixels may not have been detected, a geodesic morphological operation was applied in several iterations in order to intelligently identify lane lines to mark the boundaries of driving. After identifying the expected road regions, the edges of potential objects were identified by finding differences in the two images produced, based on the assumption that they would capture left and right edges, respectively. Then the edges were matched on a combined view to provide a bounding box for identified objects. Under the assumption that the road remains flat, this object detection and lane identification scheme was proven effective even in areas of significant shadowing and different textures. After developing the specific algorithms to detect obstacles and lane lines, the images were reoriented to provide a real-time view of free space for the vehicle.

Applicability

This paper contains many useful processes involving stereoscopic obstacle detection as well as useful morphological operations used to extrapolate on noisy line detection data. This paper also elaborates on the minor details of the costs and benefits of set up configuration and initialization. For example, there is an advantage to improving long-range obstacle detection by increasing the spatial separation between the stereo cameras; in contrast this also increases the area of the regional blind spot between the two cameras and the intersection of their viewing angles. Another interesting process elaborated upon is the use of image distortion and spatial correction for correlating the pixels of the road or path into a 2-D planar surface, along with a list of useful assumptions and simplifications. By altering the patterns detected lines into what could be seen by observing the environment from above, it is possible to more readily detect their smooth continuous nature and meticulously even spacing.

Issues

Some specific issues we identified within our project thanks to the analysis of this paper are listed below.

- Hardware set up: constructing a similar experimental setup involving two identical parallel planar cameras and mounting will require extra time.
- Calibration and image processing: in order to reach the point where we can construct our algorithms and image recognition processes, we need to first manipulate the raw data into meaningful space that is best suited for our future work. This involves distorting the image into

a proper representation of 2-D space, as well as implementing physical approximations and calibration methods.

- Performance: by implementing everything in software we are allowed to be very flexible and adaptable, but we may not be able to match performance and processing speed that dedicated hardware can provide. Although this paper was published in 1998, maintaining a similar level of performance under continuous operation may be difficult but desirable.

Citations:

M. Bertozzi and A. Broggi, “Gold: A Parallel Real-Time Stereo Vision System for Generic Obstacle and Lane Detection,” IEEE Trans. Image Processing, vol. 7, pp. 62-81, 1998..

Summary

The Red Raven 2.0 robotic platform competes at the Intelligent Ground Vehicle Competition (IGVC) and focuses on different aspects of image processing and recognition necessary to detect edge boundaries and obstacles ranging from trashcans to construction barrels. They used a parallel flowchart approach that started by filtering out grass and obstacles in their pre-processing stages. They used RGB and HSV thresholds to detect lines and obstacles necessary for the creation of separate types of filters. Once a grass filter and an obstacle filter were created, the obstacle filter was subtracted from the grass filter to create an image that only displays the white lines. The Red Raven team then proceeded to pass a small particle filter to reduce the noise from discontinuous areas or random bright spots in the grass. After they created an image that only contained the distinguishable white lines, they applied a Canny Edge Detection algorithm to obtain edge information. The team then used a convex hull operator to create an image of solid non-discontinuous lines which then they applied another small particle filter to remove noise in the lines. Finally, the team corrected for the distortion of the line image by converting it into a polar histogram which contains information about the line boundaries.

Applicability

The Rose-Hulman Robotics Team is in the procedure of building an intelligent ground robot. Since our type of application also involves the IGVC, most of the features mentioned in this paper are potentially useful. The most significant feature about the approach mentioned in the paper was the parallelism of the obstacle and line detection. This will help us reduce processing time which can be used to achieve a quicker and faster response from our robot.

Issues

One of our main concerns is that the actual environment where the robot will be performing does not consist of uniform grassy field. Discontinuities in the grass, such as brown patches of grass, might not be detected by the grass filter and might pass as an obstacle. Other potential problems consist of the brightness that the camera will experience. Bright spots of light created by the horizon line or reflective surfaces might fool the algorithm into thinking that it is a white line. Finally, since the line detection is dependent on the obstacle detection filter, if the obstacle detection filter fails, the line detection will also fail.

Citations:

Anikstein, Alex et al. IGVC. "Red Raven 2.0." California State University, pp. 9 – 11. June 2012.