MODELING ENVIRONMENTAL UNCERTAINTY IN GROUND ROBOT NAVIGATION

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Abstract

The Missouri University of Science and Technology (formerly University of Missouri-Rolla) Robotics Competition Team has developed an innovative solution to the challenge presented by the Intelligent Ground Vehicle Competition. The challenge calls for a ground robot to navigate an obstacle course consisting of boundary lines and upright obstacles. The obstacle course, arranged on a grass field bounded by painted lines, includes construction barrels, heavy-duty netting, cones, trees and simulated potholes. This competition expects students to focus on advanced path planning, control, and vision algorithms. The base system can be extended with higher-level learning algorithms for any ground vehicle platform. The team's solution is to have the robot develop two models of its environment. The first is simply a map of the obstacles detected by the robot's sensors. The second records the uncertainty of each region in the obstacle model. These models are populated by a vision system and accessed by an intelligent control system to drive the robot. This allows the team's omni-directional robot to look in areas of low certainty while driving in areas of low cost, thus making the robot seem curious and intelligent in its environment.

Introduction

The Intelligent Ground Vehicle Competition (IGVC) sponsored by AUVSI presents an interesting challenge to university students. Except for physical dimensions and safety, there are few design constraints. The teams must decide for themselves how to detect obstacles and avoid them. The Missouri University of Science and Technology has designed and constructed a two-wheel drive robot to answer this challenge. In keeping with previous Missouri S&T robots, the team has chosen to use stereovision cameras to sense the environment. The design was chosen for its elegance and simplicity: passive vision sensors can sense more of their environment with less power and impact, tank drive is simple to construct and easy to control. This robot is a stable platform that Missouri S&T can use to test sensors and algorithms. It is even able to serve as a prototype platform for navigation software for more complex robots.

Primary Sensing

Primary sensory perception is accomplished through a stereovision camera. The camera uses disparity calculations to calculate the locations of objects in three dimensions. This data is transformed into a height map of the robot's surroundings. If the environment were completely flat then this map could be used to find all of the obstacles in the area. To allow the robot to navigate in uneven terrain, the derivative of the height map is taken to make a slope map. Areas with very large slopes are defined as obstacles, whereas areas with smaller slopes are assumed to be minor terrain changes. A filtering algorithm is applied to ignore regions of the terrain with low slope. White lines are passed through the filter and are considered lethal. This filtering results in the elimination of unimportant regions in the camera's view.

Secondary perception is performed using an array of monocular web-cams. These cameras fill in the blind spots of obstacle detection around the robot. Using a simple object detection algorithm, the extra cameras are able to provide rudimentary information around the sides of the robot.

In order to accurately navigate a given environment, accurate positioning data is a must. To this end, the current setup uses GPS units to help provide as accurate positioning data as possible. The GPS units themselves will each experience some amount of error due to atmospheric interference. To combat this problem, the data from the GPS units is filtered in order to gain a more accurate position. The filter used is the Kalman filter, which provides an estimate based on an adaptive weight system. This takes into account whether or not the incoming sensor position data is more accurate than the predicted position of the robot. The Kalman filter also provides a measure of the accuracy of its filtered data. The Kalman filter can also be fed data from multiple sensor sources. In particular, the GPS units are providing the raw positioning data, while the wheel encoders provide an estimated current speed. The position data from the GPS is fed directly into the filter, while the other sensor data is used to make a more accurate prediction of the robots next position. In this manner, the Kalman filter is made more accurate, which makes the positioning data more accurate, and ultimately, makes navigation more accurate and faster.

The robot utilizes a new statistical model to capture and maintain the state of the environment by estimating a confidence value at each observed location. As observations at a given location are accumulated, the variance over all observations at that location is calculated and used as a confidence measure to bias the cost of traversing that location. For instance, locations with a high variance have a low confidence and the cost of those locations is biased towards a medium-level cost. By biasing towards a medium cost, any path planning algorithms will not take actions based on faulty information, in the form of either high or low cost. By incorporating the variance of observations into the cost calculation, the environmental model becomes robust to both sensor noise and accumulated pose errors.

For a set of n observations, X, the variance of the observations is calculated by:

$$S^2 = \frac{1}{n-1}\left[\sum_{i=1}^{n}\left(X_i - \bar{X}\right)^2\right]$$

Mean:

$$\bar{X} = \frac{1}{n_1}\sum_{i=1}^{n_1} X_i$$

Finally, the cost is calculated as follows:

$$C = \overline{X} - 2\overline{X}S^2 + S^2$$

Figure 1 shows the cost function characteristics under varying levels of data mean and variance. Note that as the variance increases, the evaluated costs, which can be interpreted as a probability of the existence of an obstacle, tend toward 0.5. This prevents any planning algorithms from making decisions based on high-varying, faulty information.

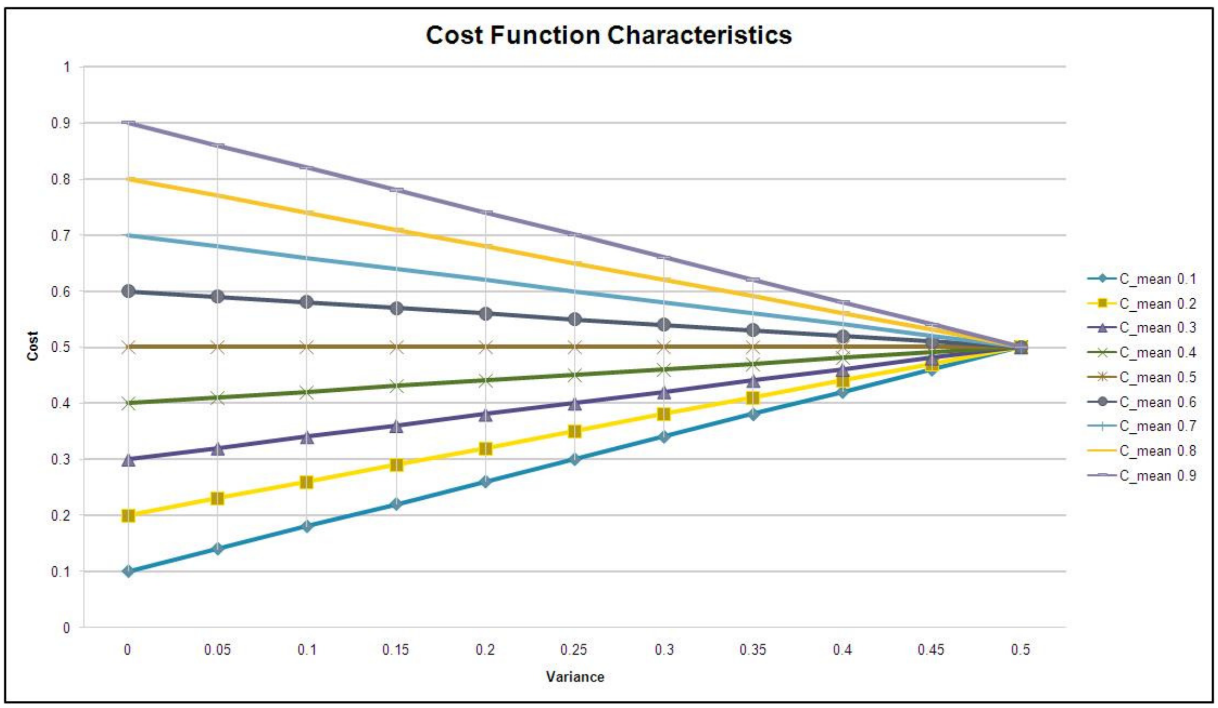


Figure 1. Cost Function Characteristics

Environmental Modeling Comparison

The Confidence model was compared with an accumulative model under simulation in the Player-Stage robotic simulation environment. Gaussian noise with variance of 0.25 and a mean of 0.75 was used for all detected points, and the position of the robot to simulate perception and pose error.

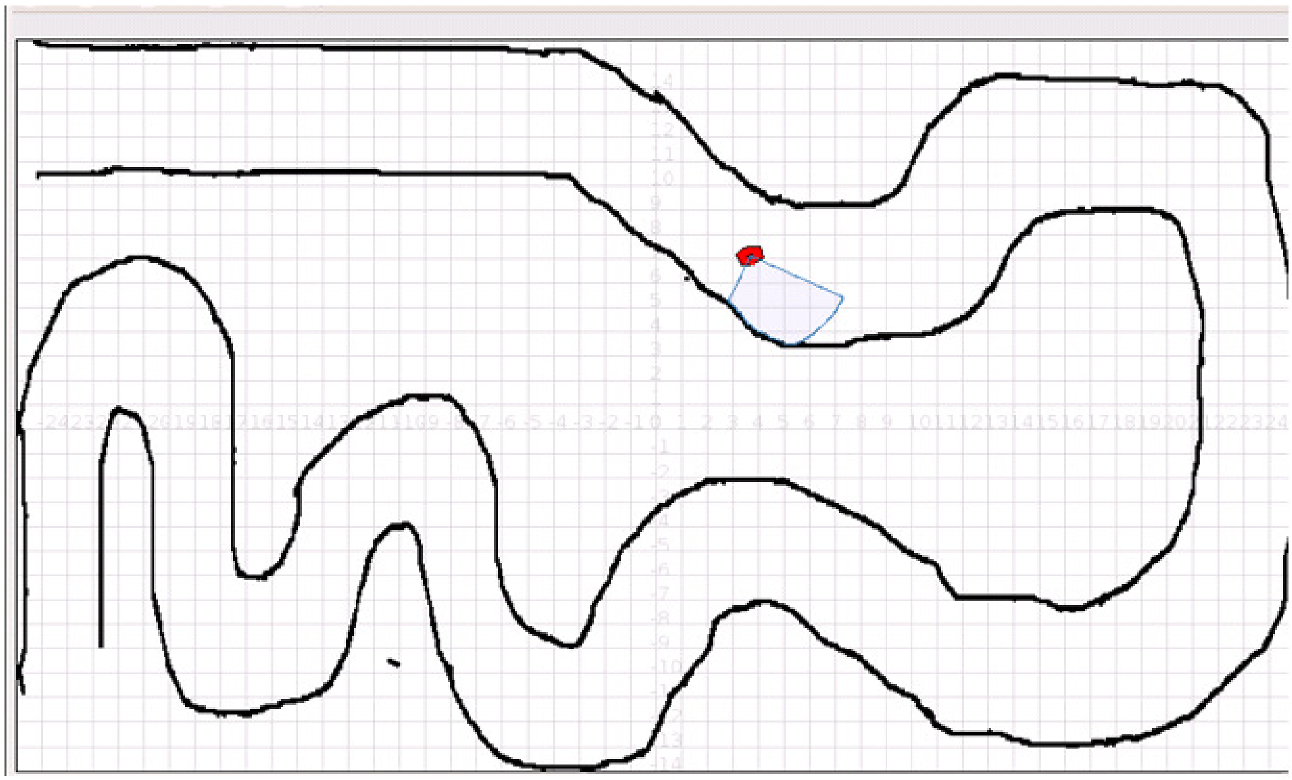
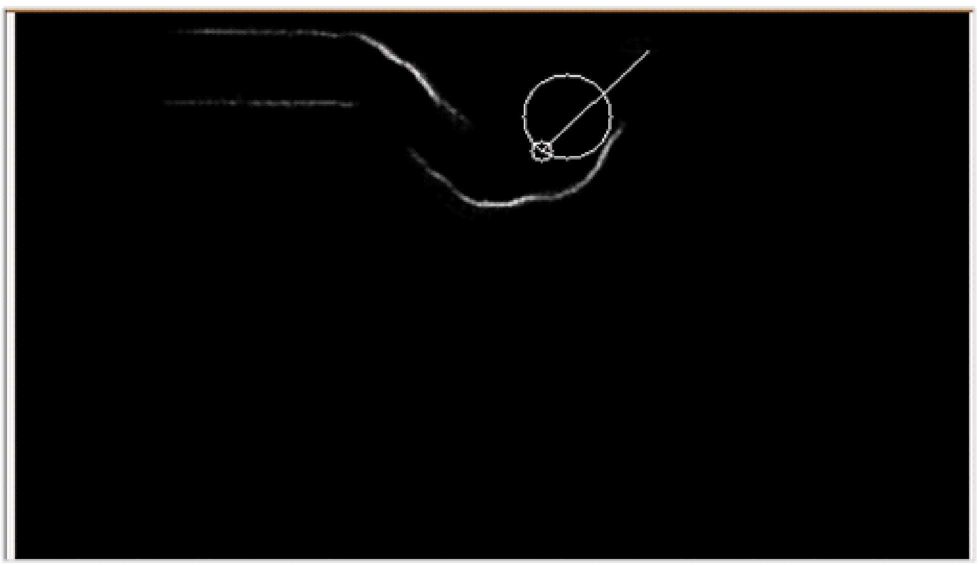
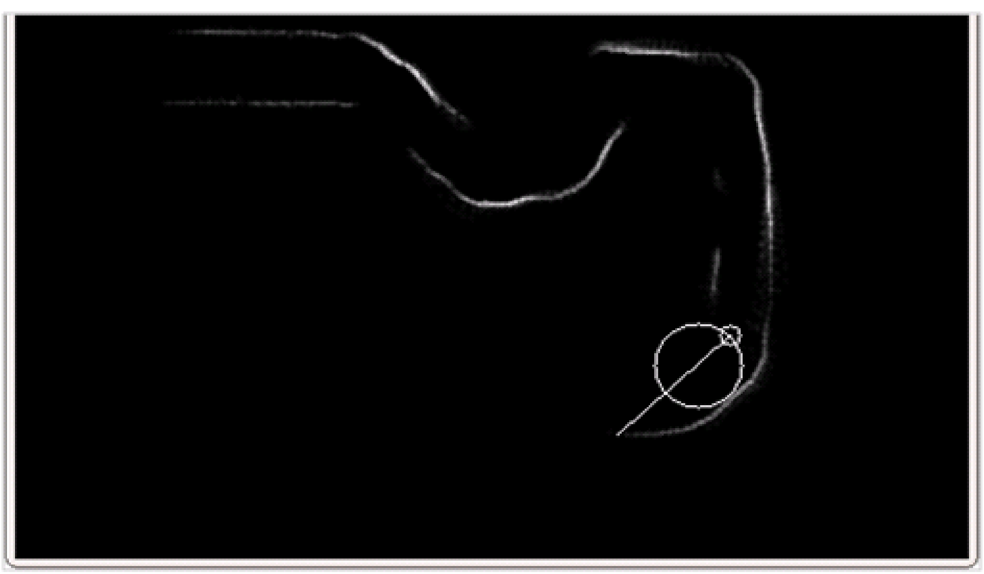


Figure 2. Player-Stage Evaluation Environment

Figure 3 illustrates the performance of the accumulated model. Notice that the model is initialized with assumed low cost, and thus information about the quality and quantity of acquired observations is lost.





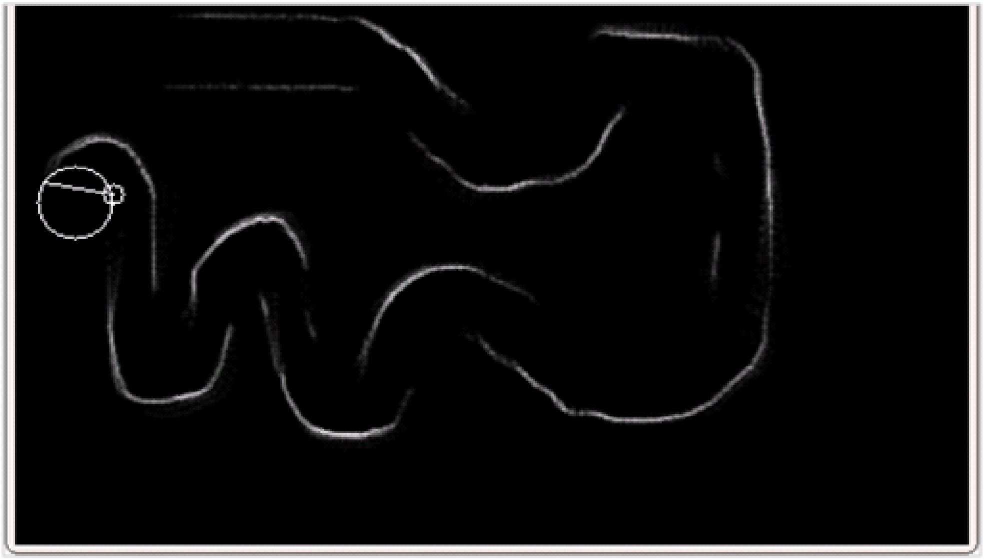
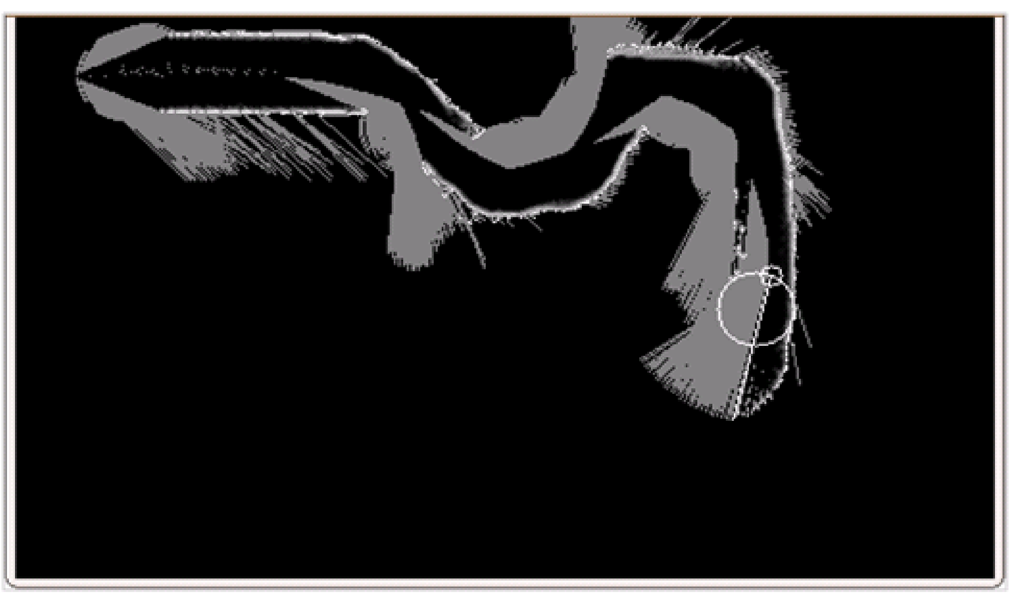


Figure 3. Accumulator Model Execution

Figure 4 illustrates the performance of the confidence model. The brightness of the image indicates the cost evaluated at that point. Note the gray areas of the image - these are locations which were evaluated by the planning software, but because there were few or high-varying observations at those locations, the model returned a 50% cost for those locations. This information can be further utilized to direct the sensing of a high-mobility platform.



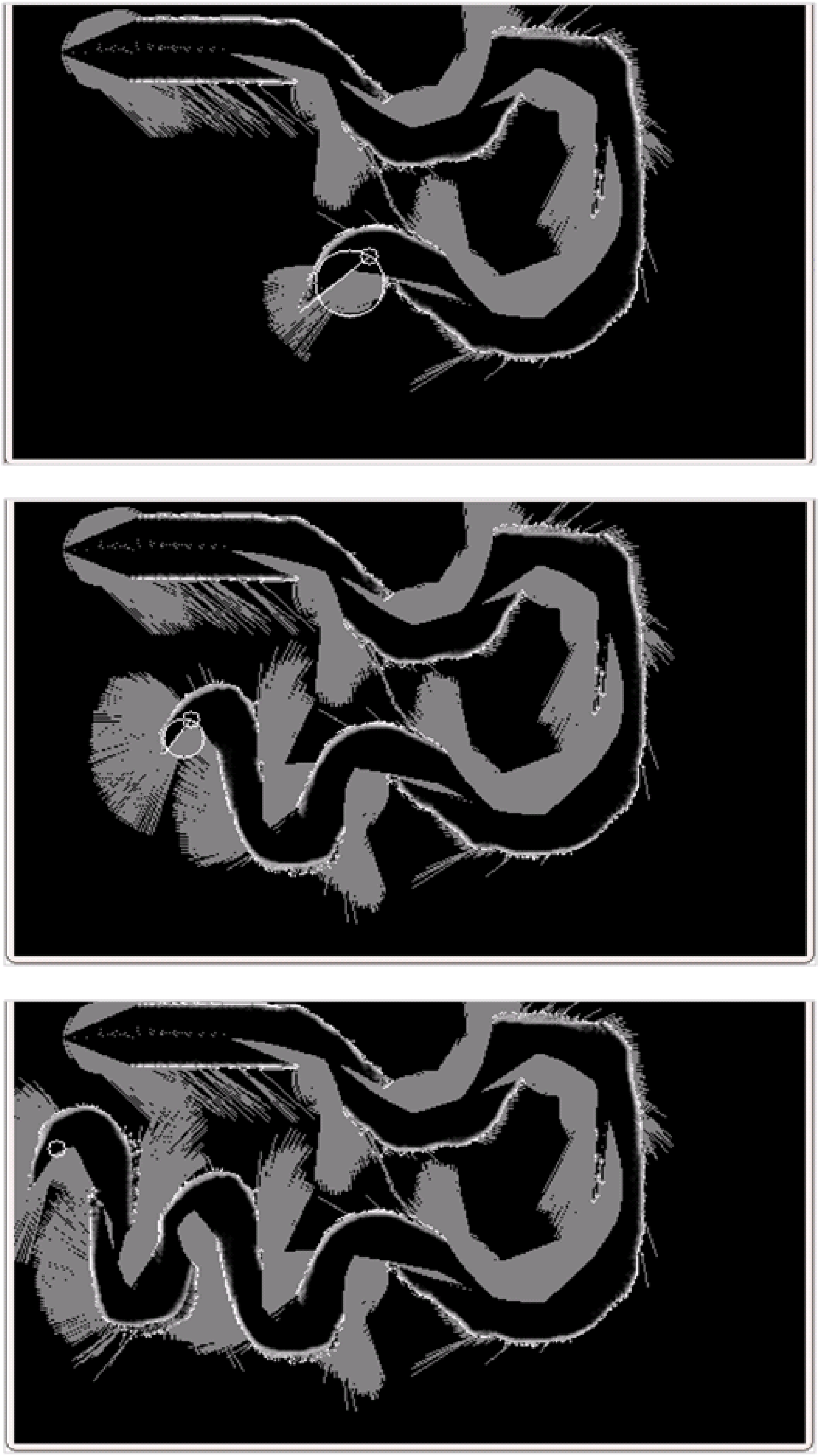


Figure 4. Confidence Model Execution

Conclusion

The Confidence model is able to provide a high-quality environmental state with built-in noise filtering, as well as providing extra information about uncertain areas that can be used to drive complex sensing-based behaviors in mobile robotics applications.