

The algorithm is related to other motion and velocity estimation algorithms, but is different because the data processed is 3D points, not camera images. This difference in input data makes a large difference in how feature selection and correlation are implemented. The algorithm also must handle oblique viewing angles and rel-

ative high sensor noise; both of these make HRN challenging. Finally the HRN algorithm actually commands the lidar to collect data during descent that is the best for HRN. This “Active Vision” approach was not used in previous work.

*This work was done by David M. Myers, Andrew E. Johnson, and Robert A. Werner of*

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*The software used in this innovation is available for commercial licensing. Please contact Daniel Broderick of the California Institute of Technology at [danielb@caltech.edu](mailto:danielb@caltech.edu). Refer to NPO-47115.*

## Tracking Object Existence From an Autonomous Patrol Vehicle

**These techniques could be part of a mobile surveillance system attached to a ground vehicle, boat, or airplane.**

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An autonomous vehicle patrols a large region, during which an algorithm receives measurements of detected potential objects within its sensor range. The goal of the algorithm is to track all objects in the region over time. This problem differs from traditional multi-target tracking scenarios because the region of interest is much larger than the sensor range and relies on the movement of the sensor through this region for coverage. The goal is to know whether anything has changed between visits to the same location. In particular, two kinds of “alert” conditions must be detected: (1) a previously detected object has disappeared and (2) a new object has appeared in a location already checked.

For the time an object is within sensor range, the object can be assumed to remain stationary, changing position only between visits. The problem is difficult because the upstream object detection processing is likely to make many errors, resulting in heavy clutter (false positives) and missed detections (false negatives), and because only noisy, bearings-only measurements are available. This work has three main goals:

(1) Associate incoming measurements with known objects or mark them as new objects or false positives, as ap-

propriate. For this, a multiple hypothesis tracker was adapted to this scenario.

(2) Localize the objects using multiple bearings-only measurements to provide estimates of global position (e.g., latitude and longitude). A nonlinear Kalman filter extension provides these 2D position estimates using the 1D measurements.

(3) Calculate the probability that a suspected object truly exists (in the estimated position), and determine whether alert conditions have been triggered (for new objects or disappeared objects). The concept of a “probability of existence” was created, and a new Bayesian method for updating this probability at each time step was developed.

A probabilistic multiple hypothesis approach is chosen because of its superiority in handling the uncertainty arising from errors in sensors and upstream processes. However, traditional target tracking methods typically assume a stationary detection volume of interest, whereas in this case, one must make adjustments for being able to see only a small portion of the region of interest and understand when an “alert” situation has occurred. To track object existence

inside and outside the vehicle’s sensor range, a probability of existence was defined for each hypothesized object, and this value was updated at every time step in a Bayesian manner based on expected characteristics of the sensor and object and whether that object has been detected in the most recent time step. Then, this value feeds into a sequential probability ratio test (SPRT) to determine the “status” of the object (suspected, confirmed, or deleted). Alerts are sent upon selected status transitions. Additionally, in order to track objects that move in and out of sensor range — and update the probability of existence appropriately — a variable “probability detection” has been defined and the hypothesis probability equations have been re-derived to accommodate this change.

Unsupervised object tracking is a pervasive issue in automated perception systems. This work could apply to any mobile platform (ground vehicle, sea vessel, air vehicle, or orbiter) that intermittently revisits regions of interest and needs to determine whether anything interesting has changed.

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