Unexploded Ordnance Detection

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Introduction

Unexploded ordnances (UXOs) can be found in over 23,000 square miles in the US alone. This area encompasses nearly 2,300 sites which are mainly composed of troop training areas, weapons testing sites, and munitions storage facilities. Around the world, the land area covered skyscrapers as you start including battlefields. Because of their inherent explosive nature and the potential environmental impact, these UXOs need to be found and disposed of before the land can be safely utilized by civilians.

The US alone spent over $250 million last year in cleaning up UXOs, and it is estimated that the final cost of cleaning all of the US’s contaminated lands will be approximately $25 billion.

My research focuses on designing a more efficient and robust UXO search strategy based on Bayesian filters.

Search Strategy

Mag and Flag (1998)
A technician would walk systematically through a field with a metal detector and drop a flag whenever the sensor beeped. The technician would later come back and dig up the area in hopes that he found a UXO.

For every 100 false positives, there was 1 true positive. Because of the cost of each excavation, improving this false alarm rate is what most current UXO research is focused on.

Proposed Technique (2007)

Full coverage pass with sensors mounted on a manned vehicle

Post-processing

Intelligent interrogation of possible UXO locations

Excavate suspected UXOs

Proposed addition

Based on current estimate, optimally place sensor

Take new readings and revise estimate

Sigma-Point Filter

Because of the non-linear nature of the magnetometer sensor model, the Sigma-Point Filter (Unscented Kalman Filter) was chosen as our estimator. As stated in the literature, the Sigma-Point Filter has the advantages of handling non-linear equations better and not requiring derivatives when compared to the typical Extended Kalman Filter. However, just like the Extended Kalman Filter, it is a biased estimator as we will see below.

Sigma-Point Filter

Magnetometer

The above equation represents the magnetic field produced by a magnetic dipole. This is used in industry as a simple model of the magnetic signature created by a UXO. The magnetometer will sense the component of the magnetic field that is normal to the sensor and report back the component’s magnitude.

The main sensors used in detecting UXOs are electromagnetic induction sensors, magnetometers, and ground penetrating radars. We are using the magnetometer for our initial studies.

Cost Function

Given the sensor model shown above, a cost function was developed that will quantify the uncertainty in an estimate of the UXO parameters based on a set of magnetometer readings. This cost function is built on the Extended Information Filter (EIF) which is equivalent to the commonly used Extended Kalman Filter. By minimizing the cost function below, we are determining the optimal placement of our sensors which will produce our best possible UXO estimate.

As a sanity check, we applied this optimization procedure to a range sensor. This is analogous to several underwater buoys trying to find a stationary target with a very simple sonar setup. In the left plot, we have two sensor buoys. By minimizing the cost function, the algorithm tells us that the ideal placement of the sensors are such that they are separated by 90 degrees. The right plot assumes we have three buoys. In that case, the algorithm separates the buoys by 60 degrees.

Optimal Placement for 2 Range Sensors

Optimal Placement for 3 Range Sensors

Two trial runs are shown above. Both consist of 4 magnetometer readings and one UXO target. The magnetometers were fixed in their position, but allowed to rotate. What you see pictured is the resulting estimate after all 4 magnetometers have taken their readings and an estimate of the UXO’s position was calculated.

For the left plot, the sensors were all fixed in orientation. This simulated what you would see in the field as you drove a sensor over the field looking for UXOs. In the right plot, we implemented our cost function into deciding how to orient the sensors. The left most sensor took its reading first. Then, the algorithm optimized the second sensor’s orientation based on what it learned from the first sensor. This progressed until all 4 sensors had taken their readings. This process is equivalent to driving over a UXO with a magnetometer, but this time allowing the magnetometer to rotate itself intelligently.

In both cases, the estimate of the UXO’s initial position was (1, -0.5) when it in fact was (0,0). In the constant orientation case, the estimator clearly diverges. For the second case, the estimator approaches the actual UXO location and it envelopes the UXO in its 90% confidence ellipsoid. The reason the estimator does not converge is because of the inherent bias of the algorithm. This bias can be eliminated by then doing a non-linear least squares search that optimizes the final estimate. When the non-linear least squares is applied to the first case, the solution diverges.

Conclusions

We have demonstrated that a cost function based on the Extended Information Filter can be used to improve UXO detection. We have also shown that a Sigma-Point Filter can be used as a UXO location estimator.

Possible Applications

Because of the nature of the cost function, this algorithm can easily be extended to incorporate multiple vehicles and multiple sensors as long as good equation models exist. Some possible future applications include: autonomous rescue beacon locator, mine clearance, and autonomous docking.

Acknowledgements

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