Link Foundation Fellowship Report

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Narrative

Introduction

Magnetic anomaly detection (MAD) is a leading technique for the detection and localization of obscured magnetic targets via exploiting the field anomalies they create. This is especially true in marine environments when looking for unexploded ordnance (UXO), because the DC magnetic field is not highly influenced by numerous types of media (i.e. water) or weather conditions. MAD is also a passive technique, which allows it to go unnoticed by the target. Whereas current applications of MAD have been shown to be effective for localizing single targets at a time, the development of a method for multiple localization would the robustness of magnetic surveys in ocean environments. To accomplish the separation, an algorithm for independent component analysis (ICA) was tested using a magnetometer attached to an autonomous underwater vehicle (AUV).

Algorithm Pipeline

The general flow of the algorithm pipeline can be seen in Fig. 1 and resembles a matched filter approach. The ICA takes in observed data and generates estimated signatures of the separate targets. Meanwhile, a genetic algorithm (GA) is used to propose various potential solutions for comparison. Using mean squared error (MSE) as the comparison criterion, the best match between the ICA and GA is chosen as the solution.

Figure 1: The algorithm pipeline shows how two different tracks: the ICA track and the GA track. ICA solutions are compared against various GA proposals using an MSE criterion and the best match between them is the chosen solution.
ICA algorithms are considered a blind source separation technique because a priori information on the nature of the sources or the mixing matrix is not needed for the solution. ICA represents the observed data in a statistical domain where the information is projected on a set of statistical criteria used to imply independence. Various assumptions are used for problems of this nature, including:

- sources and noise are stationary and zero-mean
- sources are statistically independent
- noise is independent of the sources
- number of sensors exceeds or equals the number of sources ($M = N$)

In real applications, some of the assumptions may be violated and therefore additional information may need to be provided.

Consider an experimental set-up where magnetometers record multiple targets according to:

$$x(l) = As(l) + n(l)$$

where $l$ is the independent variable of position, $x(l)$ is a set of $M$ sensor recordings, $s(l)$ is a set of $N$ source signals that cannot be directly observed, $n(l)$ is additive noise and $A$ is a mixing matrix. In this example, the mixing of the signals is assumed to be linear. In this case, the goal is to generate an inverse to the mixing matrix $A$, denoted as $W$, that can provide a suitable separation of the source signals.

With each iteration of the algorithm, the measure of independence is maximized based on higher order statistics. A typical choice is the fourth order moment called kurtosis, or the relative flatness of a peak compared to a Gaussian distribution. The justification lies in the Central Limit Theorem, which suggests that the sum of independent random variables has a distribution with a higher degree of gaussianity than each individual variable. Therefore, it is implied that independence can be derived by separating the sum and maximizing non-gaussianity.

**Results**

Simulations were first used to vet the algorithm and modeled using a Remus 100 AUVs with attached magnetometers. It is important to note that while multiple vehicles were assumed in initial simulations, this was not possible due to only having one operational vehicle and one magnetometer. The ocean floor was considered flat, with $z = 0$. Thus, the z-coordinate of the simulated targets was always approximated as 0, with only the x and y coordinates being variable. These targets were placed anywhere within a 50 by 50-meter region. The magnetic moments were all set to the same value. The vehicle was always oriented in the x-direction and moved in a horizontal straight trackline at 2 m/s. While the y offset would depend on the generated target’s placement, the z offset was set to 3 meters to match the vehicle’s chosen operation depth.

For a situation involving two targets with magnetic noise in the background, three magnetometer records were generated because the noise is also considered a source. A generalized diagram of this set-up can be seen in Fig. 2 and Fig. 3.
The records were used as inputs for the ICA algorithm; it was specified for the algorithm to generate two outputs. Fig. 3-6 show an example using ICA. The outputs of the ICA and GA were scaled between 0 and 1 to avoid scaling issues common with ICA methods. The algorithm showed numerous successes in localizing both targets within roughly 1 to 2 meters, but failures were still common. In the failed cases, however, one target was properly localized in most cases. Refinement of the ICA algorithm is necessary to increase the success rate.
Figure 4: The estimated solutions of individual targets.

Figure 5: The first target localized.
For experiments, the vehicle set-up in Fig. 7 was used. The magnetometer is located at the very tip of the long cylindrical case attached at the nose of the vehicle. This was done to minimize magnetic interference from the vehicle. Fig. 8 shows some tracklines collected during a mission that exhibit mixed observations of multiple targets. These results are currently being fit to the algorithm pipeline developed through the simulation.
Figure 8: Experimental data showcasing observations from three tracklines.

Significance and the Future

Combining such an algorithm with magnetometers placed on autonomous underwater vehicles (AUVs) would provide the ability to quickly and accurately develop a map of magnetic anomalies in the ocean domain. Furthermore, this can be used to remove unwanted manmade objects from coastal regions. As mentioned before, this research exploits the passive nature of MAD, allowing the user to go unnoticed while searching for targets. Most of all, using a Remus 100 removes human interaction while searching for unexploded ordnance, guaranteeing safety. Since this research shows possible applications, the set-up could eventually be used to replace explosive ordnance technicians altogether.

Publications

- Multiple Localization of Unexploded Ordnance Using Independent Component Analysis (TBA)

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The support given by The Link Foundation was instrumental in providing the funding needed to purchase various sets of equipment and free up funding for additional offshore testing. This was important, as numerous tests were necessary to vet the experimental set-up and collect viable datasets. On a personal level, the support invested in me by the Link Foundation gave me the confidence I needed to develop the algorithm discussed in this report.