Classification Depth and Complex Scenarios for One-Pass AGC

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Introduction

We present recent work investigating the **depth of reliable classification** for One-Pass AGC. Using synthetic seeding we show that, given an estimate of the noise, a response curve can be used to predict classification depth at a specified multiplier of the noise. While detection depths are usually assumed to correspond to 5x noise multiplier, **our simulations indicate a 10x multiplier predicts depths at which almost all synthetic scenarios are classified correctly**.

We also investigate how **classification depth may be reduced in complex multi-object scenarios** where a deep target of interest (TOI) at the maximum classification depth is near (25 cm horizontal separation) a shallow clutter item.

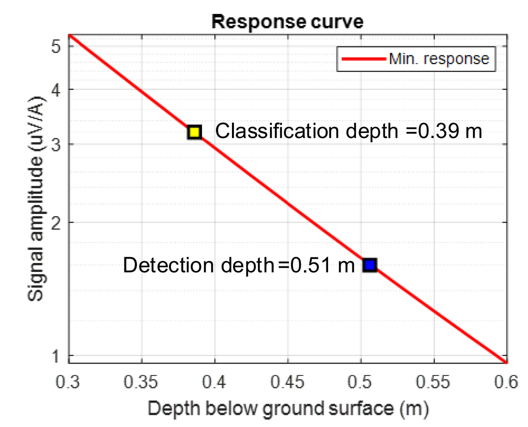
Classification Depth

Maximum classification depth depends on:

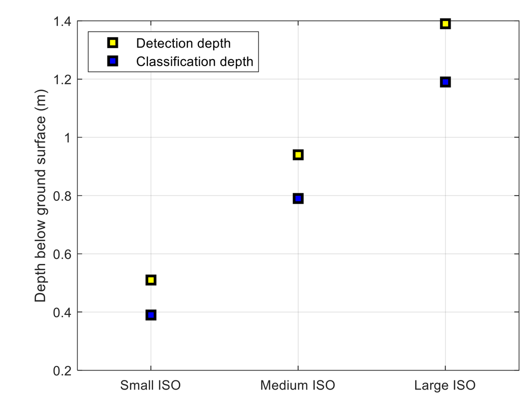
1. AGC sensor geometry and height
2. Target orientation and polarizabilities
3. Stop dig threshold
4. Noise

Response curve analysis accounts for all variables which control classification performance for single object scenarios, with a simplifying assumption that peak anomaly amplitude at a single detection channel is predictive of classification performance.

Synthetic seeding studies (see below) indicate a depth corresponding to **10x the noise** as a rule of thumb for the worst-case classification depth. This is a more conservative choice than a 5x threshold, which predicts the expected (or average) classification depth.



Response curve for a small ISO. Detection and classification depths assume 5x and 10x noise multipliers for a noise level of 0.3 uV/A for UltraTEM Portable Classifier data.



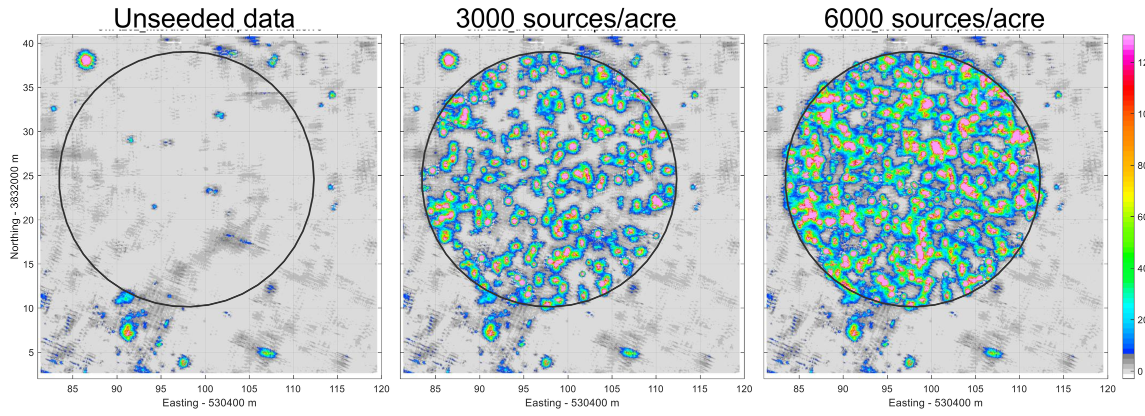
Predicted detection and classification depths for ISOs assuming 5x and 10x noise multipliers for a noise level of 0.3 uV/A for UltraTEM Portable Classifier data.

Due to the nonlinearity of the response curve, larger items see a larger absolute difference between predicted detection and classification depths.

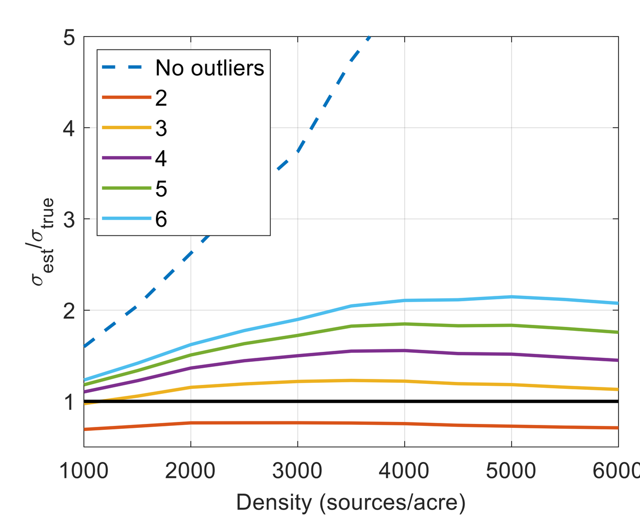
Noise estimation

A critical step in classification depth analysis is estimation of background noise. Background noise is typically estimated in dynamic AGC data by manually delineating anomaly-free areas of the data. This requires subjective decisions and may vary between analysts.

Here we consider a "trimmed" robust estimator of the noise designed to produce consistent noise estimates with minimal anomaly avoidance. This approach iteratively removes outliers that exceed a rejection threshold that is a specified number of standard deviations from zero. We also use a robust "median absolute deviation" (MAD) estimator of the noise standard deviation at each iteration.

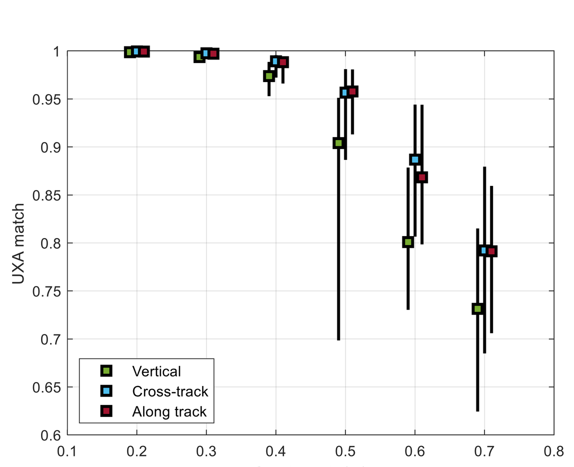


Left: UltraTEM Classifier data for testing noise estimates. We assume the estimated noise inside the black circle is the "true" noise and progressively add synthetic targets at increasing densities (middle and right) to test robust noise estimates.



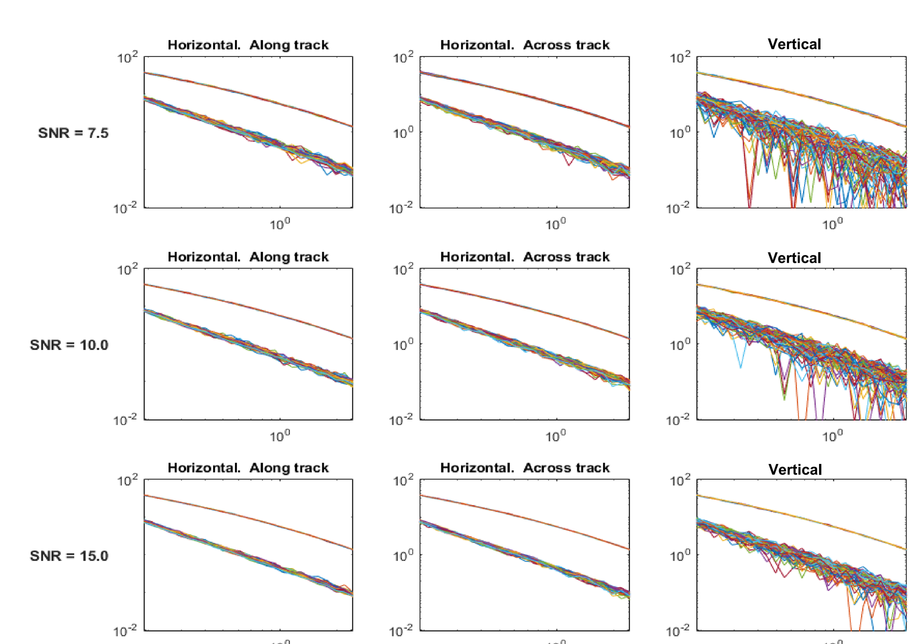
Iterative rejection of outliers can provide a nearly unbiased estimate of background noise standard deviations even at high source densities (e.g. ≥5000 sources/acre). We find that an outlier rejection threshold = 3 provides the best estimate of the background noise level for this example.

Verifying classification depth with synthetic seeding



Expected polarizability matches (using all polarizabilities) as a function of seed depth. These simulations assume Gaussian noise only.

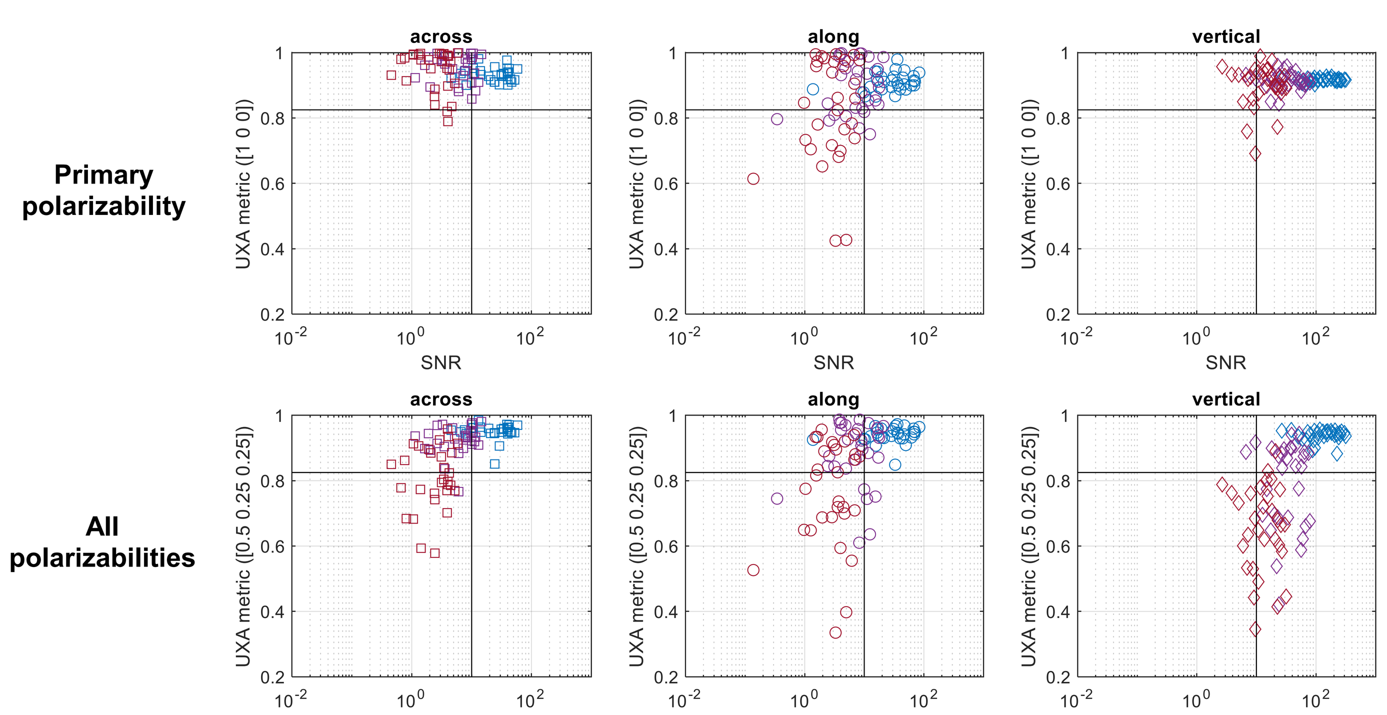
We observe lower expected polarizability matches and greater variability for vertically oriented targets.



Synthetic seeding simulations confirm that secondary polarizabilities are poorly constrained for vertically-oriented targets.

This is a consequence of weaker horizontal field excitations of secondary polarizabilities for vertical targets.

This effect is largely mitigated in classification by using primary polarizability matching.



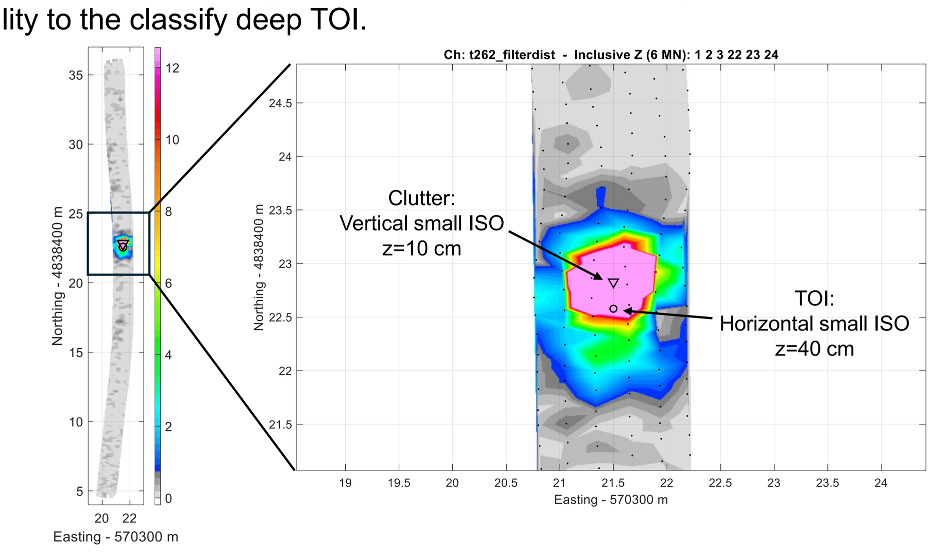
Polarizability matches for multiple realizations of synthetic seeds at varying SNR and orientation. Sources that are correctly classified at a 10x noise threshold are in the top right quadrant of each plot.

These simulations indicate that the majority of cases will be classified at the predicted maximum classification depth defined by a 10x noise threshold, provided the classifier accounts for poorly constrained secondary polarizabilities with a primary polarizability match.

Complex multi-object scenarios

Classification depth analysis accounts for site specific noise, but does not consider how classification performance may be degraded in multi-object scenarios. Here we investigate **how our ability to classify TOI at the maximum classification depth changes as the amplitude of signal from near-surface clutter increases.**

We consider the simplest case of a two-object scenario on a transect, with near surface clutter at 10 cm depth and at 25 cm horizontal separation from a small ISO at the maximum predicted classification depth of 40 cm. In the following experiments we investigate how positional error and signal from the clutter affect our ability to the classify deep TOI.

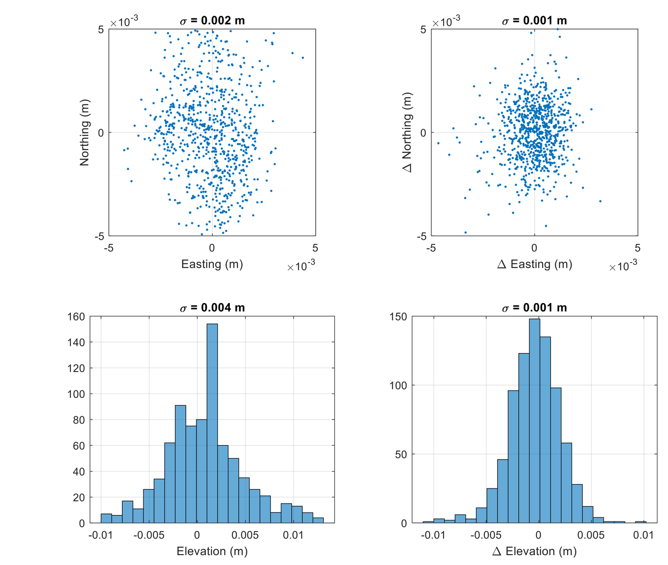


In this context **we define saturation as the peak signal of a detected anomaly relative to the peak signal from a TOI at the maximum classification depth.** For example, if we define the classification depth using a 10x noise multiplier, then a saturation value of 50 corresponds to a signal amplitude that is 500 times the noise (= 10x noise * 50). This definition will allow us to tie the saturation threshold directly to classification depth and site-specific noise.

Positional precision

Positional precision is an important control on our ability to recover accurate polarizabilities for multi-object cases when doing AGC with dynamic data (see simulation results below)

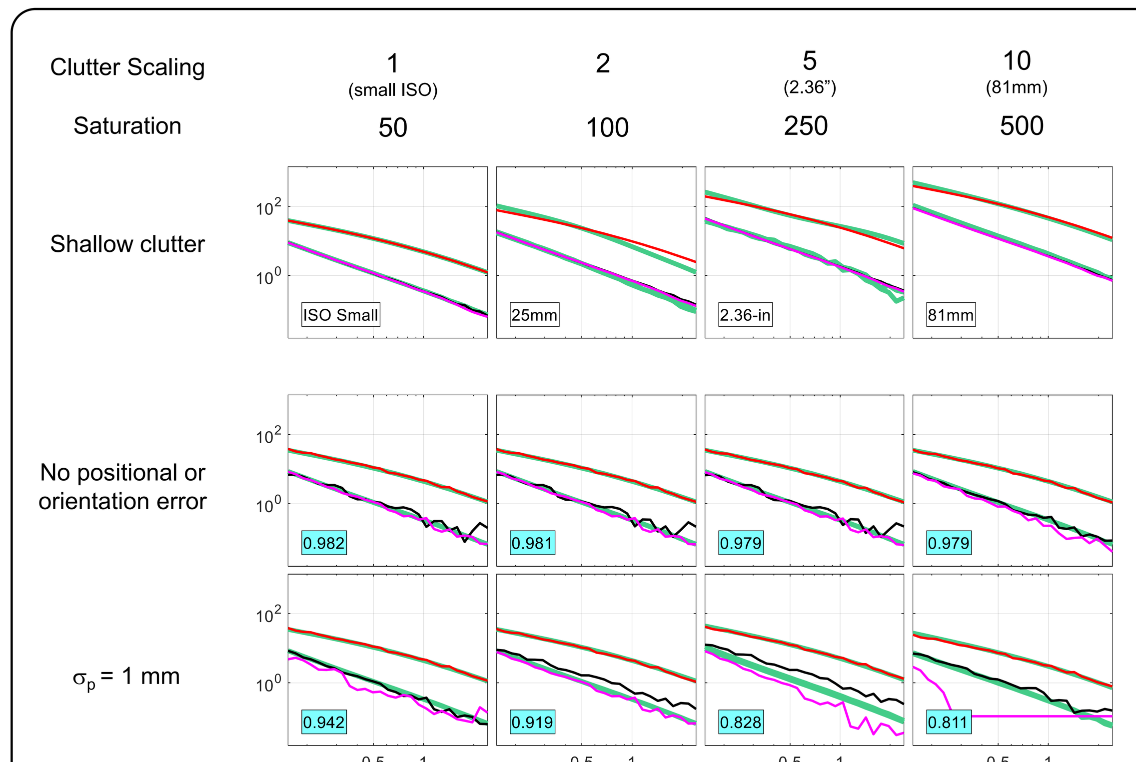
In this context we are concerned less with the absolute accuracy of sensor position and attitude, but rather the precision of these measurements as the sensor traverses over a target. To recover accurate polarizabilities in multi-object cases, we need precise measurements over a short distance (1-2 m) to minimize any spatial distortions in the measured dipolar anomalies.



Precision of RTK GPS positions during a static function test. This time series gives standard deviations of 2 mm and 4 mm for horizontal and vertical precision, respectively (left column). However, the point-to-point standard deviation in this time series is 1 mm for both horizontal and vertical positions (right column). We use this as an initial estimate of positional precision for our simulations, but also consider larger errors to account for reduced precision for a moving sensor.

Effect of saturation and positional uncertainty on classification of TOI at the maximum predicted classification depth

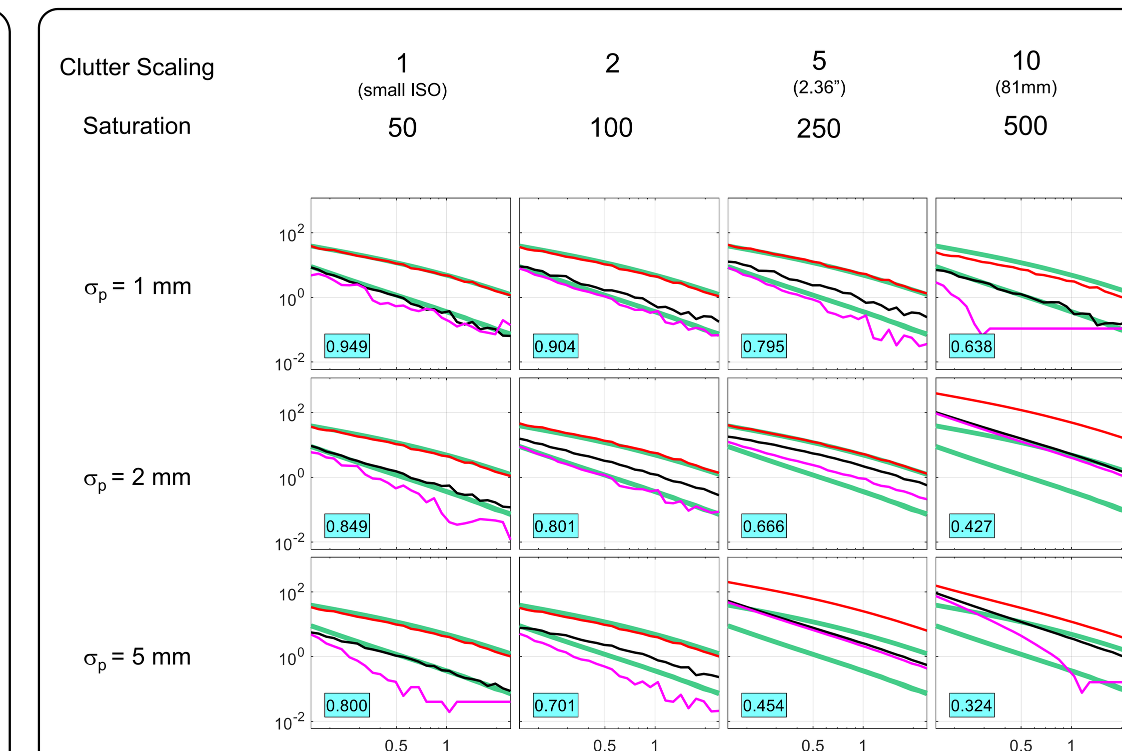
We now linearly scale the polarizabilities for the shallow clutter between 1 and 10 (as indicated by the "Clutter scaling" factor below). This scaling increases the approximate size of the near surface clutter from a small ISO to an 81mm mortar, with a commensurate increase in saturation in the data from 50 to 500. For each instance of the clutter scaling, we apply multiple realizations of zero mean Gaussian positional errors with standard deviations σ_p ranging from 0 mm to 5 mm. We also apply zero mean Gaussian errors with a standard deviation of 0.1 degrees to sensor pitch and roll. Independent errors are applied to each fiducial.



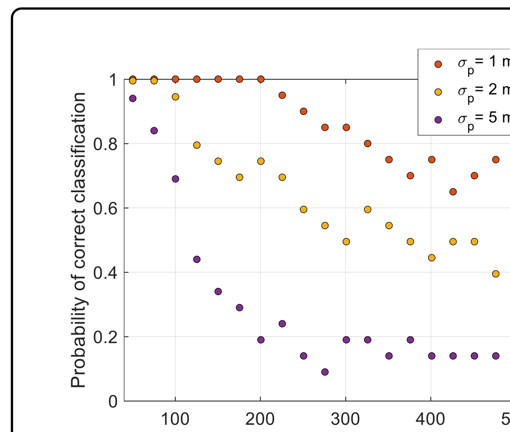
Top row: polarizabilities for near surface clutter item at 10 cm depth. We scale the polarizabilities of a small ISO up by the indicated "Clutter Scaling." This increases the corresponding saturation in the data.

Middle row: estimated polarizabilities for TOI (a small ISO at 40 cm depth). Cyan boxes indicate polarizability match using all three estimated polarizabilities. **In the absence of positional error, increasing saturation has no effect on polarizability accuracy for the range of clutter scaling (and saturation) considered here.**

Bottom row: estimated polarizabilities for the same TOI, with a positional error of σ_p = 1 mm.



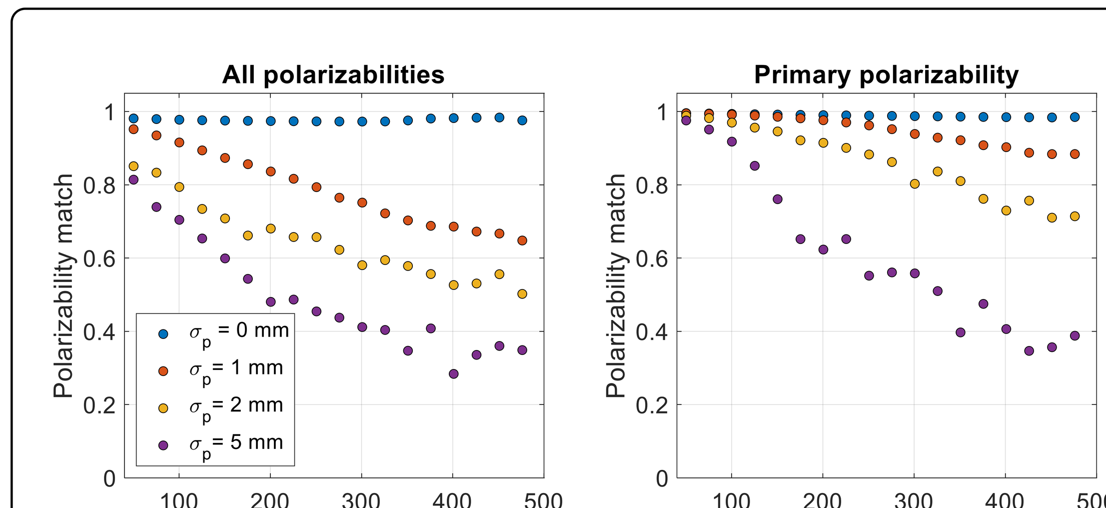
Dependence of estimated polarizabilities for TOI (a small ISO at 40 cm depth) on saturation and positional error (σ_p). **Increased saturation and positional error reduces expected polarizability accuracy.**



Probability of correct classification as a function of saturation and positional uncertainty (σ_p). Probabilities are generated with multiple realizations of positional and orientation errors for each scenarios

Here we assume that a primary polarizability match > 0.9 is required for correct classification.

A saturation threshold of 100 gives a high probability of correct classification in these scenarios.



Expected polarizability misfit as a function of saturation and positional uncertainty (σ_p). **Increased saturation and positional error reduces polarizability accuracy in multi-object scenarios.**

Conclusions

Successful one-pass classification in complex multi-object cases depends not only source separation (or density), but also:

1. **Saturation (i.e. signal of clutter relative to targets of interest at the maximum classification depth**
2. **Precision of position and attitude measurements**

Simulations indicate a saturation threshold of 100 (equal to 1000x the noise assuming a 10x noise multiplier for the classification depth). Additional measurements are recommended to needed to verify these results.