

Buried Object Classification using a Sediment Volume Imaging SAS and Electromagnetic Gradiometer

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Abstract—To advance naval capabilities in identifying buried mines and unexploded ordnance, hybrid systems that fuse data from disparate sensors are being developed. This paper describes preliminary results of a classification engine that combines target features and classification parameters from a synthetic aperture Buried Object Scanning Sonar (BOSS) and an electromagnetic Real-time Tracking Gradiometer (RTG). The target characteristics that generate signals of interest for these sensors (acoustic backscatter and induced changes in local magnetic field) are sufficiently diverse that optimal combination should effectively increase the probability of correct target classification and reduce false alarm rates. Geometric and backscatter intensity features automatically extracted from three-dimensional acoustic imagery are combined with magnetic moment and associated parameters in a joint-Gaussian Bayesian classifier (JBC), which makes mine-like/non-mine-like decisions for each contact. The fused acoustic-magnetic classifier was evaluated using a combination of sea-trial and synthetic data sets. Nine data runs were processed to yield acoustic and magnetic features, supplemented by the synthetic data. An initially large variety of feature types were down-selected by a training process to a critical subset. With this limited dataset, initial results show probabilities of false classification (P_{fc}) from 1.6% to 6.3% when at high probability of correct classification (P_{cc}).

I. INTRODUCTION

To advance capabilities in identifying buried mines and unexploded ordnance, hybrid systems that fuse data from disparate sensors are being developed. The Office of Naval Research is developing a state-of-the-art sensor suite for a Buried Mine Confirmation Unmanned Underwater Vehicle (UUV) that currently incorporates a synthetic aperture Buried Object Scanning Sonar (BOSS—developed by *Florida Atlantic University*) and an electromagnetic Real-time Tracking Gradiometer (RTG—developed by *GE Infrastructure, Security*) [1,2]. The prototype sensors are presently

being deployed and tested on a Bluefin Robotics 12.75-inch UUV as pictured in Fig. 1.

At the low acoustic frequencies necessary for penetrating the top layer of sediment (roughly less than 30 kHz), narrowband sonars exhibit limited detection performance due to coarse spatial resolution and reverberation. The BOSS system overcomes these challenges by employing low-frequency acoustics for sediment penetration, and a complement of broadband transmissions and extensive two-dimensional receive apertures for generating decimetric three-dimensional imagery. However, performance of this sonar, and indeed any seafloor-imaging sonar operating in this environment, is limited by surface and bottom reverberation, the opacity of coarse bottom substrates, and the large number of clutter objects detected.

Addition of a magnetic sensor, as in the BOSS-RTG suite, provides overlapping capabilities of target detection and localization as well as indirect information on the composition of objects. While the acoustic sensor is typically better at localization and shape estimation, RTG localization and magnetic moment estimates of ferromagnetic targets are unaffected by seabed type. At the short ranges (several meters) for which this device is designed to operate, the RTG

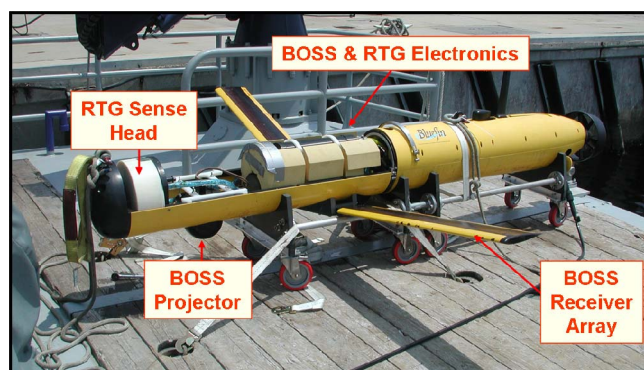


Figure 1. BOSS-RTG installed on Bluefin 12.75-inch UUV.

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can detect buried ferrous mines as equally well as proud, and generally exhibits lower clutter density than its sonar counterpart. If the abilities of these sensors are effectively characterized and an optimal strategy for fusing system outputs is implemented, the overall system could demonstrate unprecedented classification abilities with minimum false alarm rates. Such a strategy would exploit the independent nature of acoustic vs. non-acoustic sensors to drive down the false target rate.

This paper presents preliminary results of combining feature and classification parameters derived from outputs of the experimental confirmation UUV's BOSS and RTG sensors. In this approach, illustrated in Fig. 2, geometric and backscatter intensity features automatically extracted from three-dimensional acoustic imagery are combined with magnetic moment and associated parameters in a joint-Gaussian Bayesian classifier (JBC) [3], which makes mine-like/non-mine-like decisions for each contact.

Sections II and III of this paper describe the BOSS and RTG sensors and their respective detectors; Section IV presents the joint-Gaussian Bayesian classifier; Section V describes field and synthetic data used for this work; Sections VI and VII summarize target classification results and plans for follow-on efforts.

II. SYNTHETIC APERTURE BURIED OBJECT SCANNING SONAR

The BOSS is a broadband frequency-modulated sonar that generates multi-aspect imagery of buried, partially buried and proud targets using an omni-directional projector that transmits pulses in the band of 3 to 20 kHz, and hydrophone arrays embedded into towed-body wings that measure energy backscattering from the seafloor and sediment volume (Fig. 1). Three-dimensional SAS imagery is generated using a navigation solution based on measurements from a Doppler Velocity Log (DVL) and an Inertial Measurement Unit (IMU) to time-delay and coherently sum

matched-filtered phase histories from subsurface focal points over a large number of pings [4].

The focused data consist of a large set of three-dimensional SAS data cubes created by a sliding window of ping intervals, where adjacent data cubes have greater than 90% overlap. By using navigation/registration information, these data cubes are fused into a single large three-dimensional dataset, in which each voxel's intensity is equal to the maximum intensity of the co-registered voxels across all original data cubes. For improved image contrast, the intensity of the specular seafloor return (a shallow swath of voxels beneath the platform) is spatially nullified with an automated process employing measured backscatter statistics. Fig. 3 shows mosaics of top-view maximum intensity projections for three data runs collected over a buried target field in St. Andrew Bay FL, May 2004. Objects of interest are labeled; the rows of unmarked objects are cement blocks used for visual co-registration between runs.

Acoustic Detector

The BOSS three-dimensional object detector and feature extractor operates in two stages (top chain of Fig. 2). The first stage, highlight segmentation, is based on a mean-standard deviation statistical analysis by Maussong, Channusot, and Hétet [5] and a proximity clustering algorithm [3]. A feature extraction stage derives geometric and intensity features from every contact.

Highlight Segmentation and Clustering

The three-dimensional image is first normalized to keep the mean intensity approximately uniform across the volume. For highlights, a local mean and standard deviation is computed for each voxel. A threshold in mean and standard deviation is chosen based on the linear relation between the mean and standard deviation as defined by the best statistical fit to the clutter background voxels. Target voxels typically deviate from this fit. Voxels with a higher local mean or local standard deviation pass the threshold.

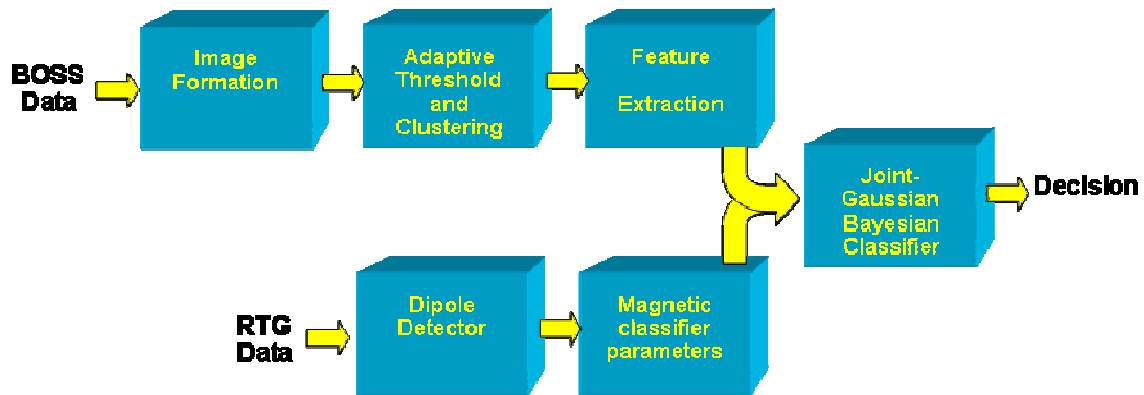


Figure 2. JBC acoustic and magnetics sensor fusion engine.

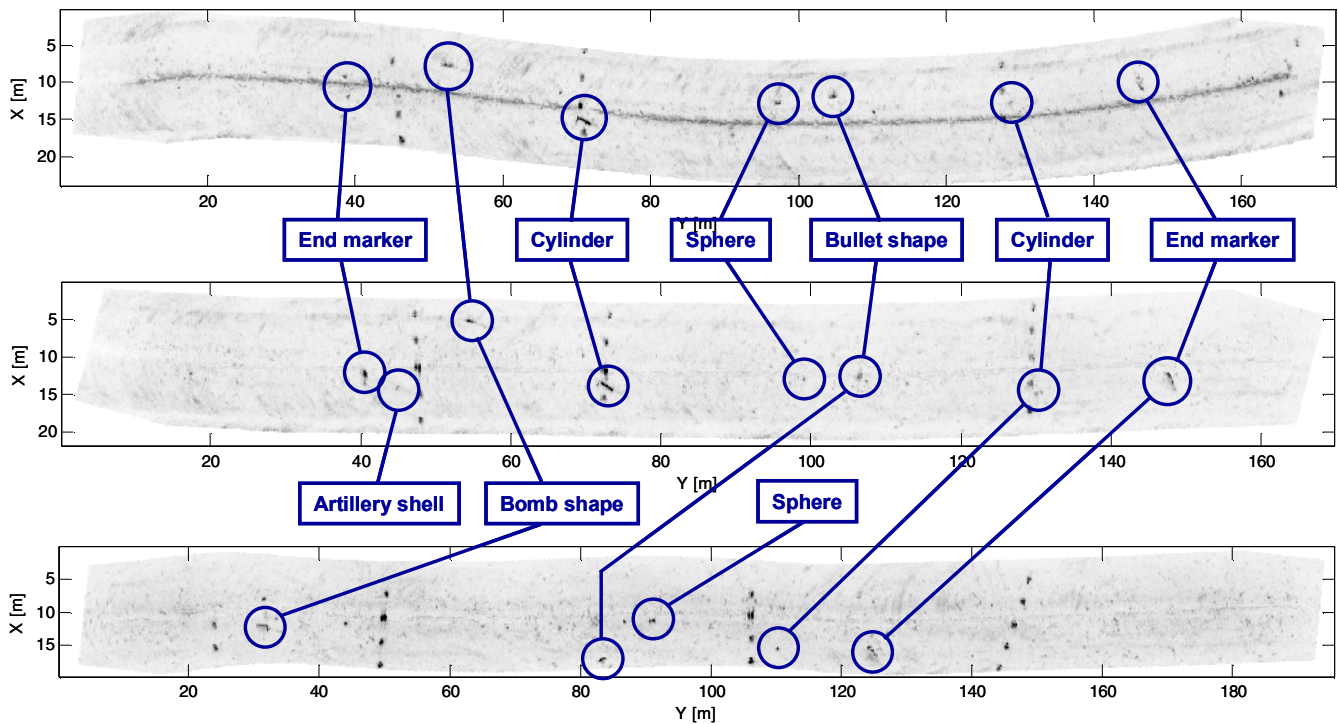


Figure 3. Acoustic data collected in May 2004 in St. Andrew Bay; run 2, top; run 4, middle; run 8, bottom.

The natural threshold between target and clutter is found at the “knee” of an entropy function—a measure of the number and compactness of voxels above a given trial threshold. The knee is defined as the point on the curve which maximizes the second derivative of the entropy. The actual threshold used for segmentation may be modified from the knee threshold in order to adjust the detector’s false alarm rate.

Voxels identified as highlights are grouped based on proximity, and all voxels within an adjustable distance are associated as a single cluster. Typically, the clustering distance is a small multiple of a voxel’s dimensions. Each cluster is passed to the feature extractor as a contact.

Feature Extraction

For each contact from the segmented image, the best-fit ellipsoid is computed via an eigenanalysis of the covariance matrix of voxel locations. This gives an estimate of the contact’s size and orientation. Geometric features include length, width, length-to-width ratio, cross-sectional area, and object volume. Intensities are normalized by the segmentation threshold to allow direct image-to-image comparisons. Intensity features include peak, total, and mean and standard deviation over the object volume.

Fig. 4 shows a rendering of the detector output near the central cylinder of Fig. 3. The cylinder is the large, central object; two of the field-marking cement blocks are located to either side. The blue lines designate the extracted major and minor axes for these objects.

III. REAL-TIME TRACKING GRADIOMETER

The RTG assembly comprises four three-axis fluxgate magnetometers that measure magnetic field anomalies caused by the presence of a target in the Earth’s magnetic field [6]. Vector-field measurements from three of the sensors, which are oriented to form an equilateral triangle, are combined to form the five independent components of the gradient tensor. The fourth magnetometer is a reference sensor used to remove effects of platform motion. The magnetic gradient time series, logged while the UUV platform is in motion, is used to detect and locate magnetically permeable objects.

Magnetic Detector

At ranges greater than an object’s physical size, the magnetic expression of an object will generally be that of a point dipole. With algorithms and software developed at the Naval Surface Warfare Center Panama City (NSWC-PC) [7], the RTG provides estimates of magnetic dipole locations, directions, and magnitudes for ferromagnetic targets. The set of dipole-moment properties can then be used as classifier features.

In general, sonar-derived target locations will be more accurate than those estimated by the RTG. To increase dipole estimation accuracy and consistency between runs, we applied a modified version of the detector which uses *a priori* input locations registered by the BOSS. Using modeled test

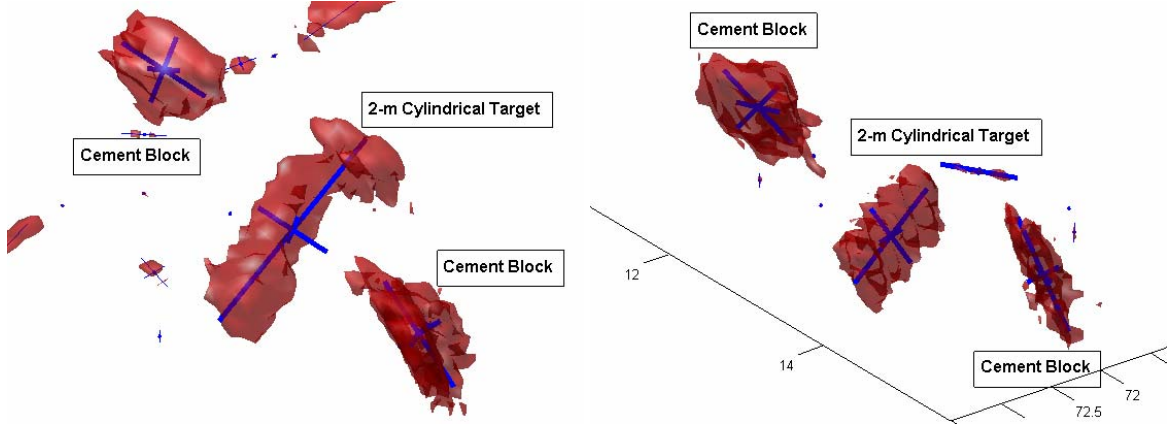


Figure 4. Detector output near the cylinder in runs 2 (left) and 4 (right) from Fig. 3. Scale is in meters.

fields to quantify this effect, we found moment estimate errors were reduced by as much as a factor of ten, depending on the proximity of multiple targets.

Magnetic field based classifiers typically use only moment magnitude. In the JBC application described here, additional calculated parameters (including several described by Lathrop, Shih and Wynn [8]) are employed, such as proxies for volume, aspect ratio, and orientation, and effective susceptibilities.

IV. JOINT-GAUSSIAN BAYESIAN CLASSIFIER

We implemented a joint-Gaussian Bayesian classifier (JBC) [3] that measures feature distributions of candidate object clusters, transforms from the original feature distributions into Gaussian distributions, computes feature covariance to exploit feature correlation, and classifies the candidate cluster as either mine-like or not, using a log-likelihood (*LLR*) test:

$$LLR = (\mathbf{x}_{\text{test}} - \mathbf{x}_{\text{clut}})^T \mathbf{R}_{\text{clut}}^{-1} (\mathbf{x}_{\text{test}} - \mathbf{x}_{\text{clut}}) - (\mathbf{x}_{\text{test}} - \mathbf{x}_{\text{targ}})^T \mathbf{R}_{\text{targ}}^{-1} (\mathbf{x}_{\text{test}} - \mathbf{x}_{\text{targ}}) + \log(|\mathbf{R}_{\text{clut}}| / |\mathbf{R}_{\text{targ}}|) \quad (1)$$

Here $\mathbf{x}_{\text{test}}$ is the transformed, measured feature vector for the candidate object, $\mathbf{x}_{\text{targ}}$ and $\mathbf{x}_{\text{clut}}$ are the mean feature vectors of the target and clutter training sets, and $\mathbf{R}_{\text{targ}}$ and $\mathbf{R}_{\text{clut}}$ are the corresponding covariance matrices of the training sets. The feature set $\mathbf{x}_{\text{test}}$ of the test object is used to calculate the corresponding *LLR* for the candidate object. The *LLR* is based on a joint least-squares covariance-weighted estimate of the difference in test detection from target and clutter mean training vectors. The value of the *LLR* is compared to a threshold to determine the test detection's membership in the target or clutter population.

To select a small but robust set of classification features from over 40 that are available, forward and backward stepwise optimal selection processes are used similar to those described in Dobeck and Cobb [9]. This stepwise process is not globally optimal, but is fast and works suffi-

ciently well. In our case, the feature subset is optimized by maximizing the integral of the ROC curve, a metric that gives weight to both *Pcc* and *Pfc*.

Note that when a particular feature is missing, due to sensor or detector limitations (e.g., a contact with sub-threshold acoustic scatter and large magnetic moment), the feature is replaced by the appropriate mean value. In Eq. 1, the missing feature is replaced by the clutter mean value in the first term and the target mean value in the second term. In each term the substituted value becomes zero after taking the difference from the mean, and the contribution to the *LLR* is zero. This procedure prevents missing features from biasing the classifier.

V. DATA

The data were acquired at test fields located in St. Andrew Bay, Panama City and during the SAX04 experiment. The fields consisted of a variety of man-made target and clutter objects, ranging in size from a fraction of a meter to several meters. Both ferromagnetic and non-metallic objects were present. The BOSS data were beam-formed using a sliding synthetic aperture window composed of 30 pings. The resulting three-dimensional image has resolution voxels 10 cm by 10 cm by 5 cm in the along-track, cross-track and depth directions, respectively. The overlapping SAS windows were mosaicked using a maximum-intensity projection onto a final three-dimensional grid (Fig. 3).

To setup the training and test data sets, the images were compared to ground truth, and each contact (defined as a bright, compact group of voxels) was identified as target, known clutter, or unknown clutter. Long, metallic contacts were labeled targets, while objects such as spheres and cement blocks were labeled as clutter. The large majority of acoustic contacts were unidentifiable and used as clutter of opportunity. Overall, twelve target and 140 clutter contacts were found in the nine acoustic platform runs used.

In one experiment, we supplement the sea-trial data with synthetic data which serves to increase the number of contacts, especially targets. The synthetic target returns were generated using a T -matrix code [10] which models the low-frequency scattering response of an elastic object. The scatterer is computed in the frequency domain, transformed into the time domain, and then beamformed using a synthetic aperture algorithm. Features were extracted from the resulting three-dimensional image for use by the classifier.

The magnetic field data used in the classifier include eleven RTG tracks collected in 2006 in St. Andrew Bay. Although additional magnetic-field data were acquired earlier, technical difficulties prevented their use. To improve the limited dataset, magnetic and acoustic contacts were matched to create the fused dataset.

In order to increase the number of objects used to train and test the JBC, we supplemented field data with simulated RTG data using AST's in-house magnetic modeling tool EMAGINE. Given a set of input dipole moments, or parameters to approximate a moment by assuming the object is a prolate ellipsoid shell, EMAGINE uses Green's function formulations to generate three-component magnetic field and five-component gradiometer data. Noise simulations include effects from water currents, geologic variability, solar activity, and generic white noise. Simulations were generated for the synthetic objects used in the acoustic simulations, as well as for BOSS data collected during the SAX04 and 2005 St. Andrew Bay experiments, for which there were no usable magnetic field data.

VI. CLASSIFICATION RESULTS

The features extracted from the acoustic and magnetic data were combined into a single feature set, which was subsequently divided into training and testing subsets for evaluating the JBC classifier. The JBC was trained and evaluated multiple times in order to test for alternative feature-set solutions: note that the mean receiver operating characteristic (ROC) curves are presented in this discussion.

Results of the JBC utilizing the sea-trial data of Sec. V are shown by the ROC curves in Fig. 5. With acoustic features only, the classifier demonstrated a 6.3% P_{fc} while at high P_{cc} . By also using magnetic features, the P_{fc} drops to 1.7%. This large improvement is due to the fact that the classifier cannot classify magnetic-only contacts using solely acoustic features. Likewise, acoustic-only contacts cannot be classified using magnetic features. (The magnetic-only ROC curve is not shown because of the insufficient number of magnetic-only contacts.)

Results of the JBC utilizing both sea-trial and synthetically-generated data are shown by the ROC curves in Fig. 6. The classifier shows similar performance with inclusion of synthetic data. The fused classifier using both acoustic and magnetic features slightly outperforms the case where only acoustic features are employed.

The system with synthetic data appears to have a higher false classification rate. This observation may be due to limitations of the models to simulate features. Alternatively, the increased number of exemplars may reflect a more realistic, more modest, estimate of performance.

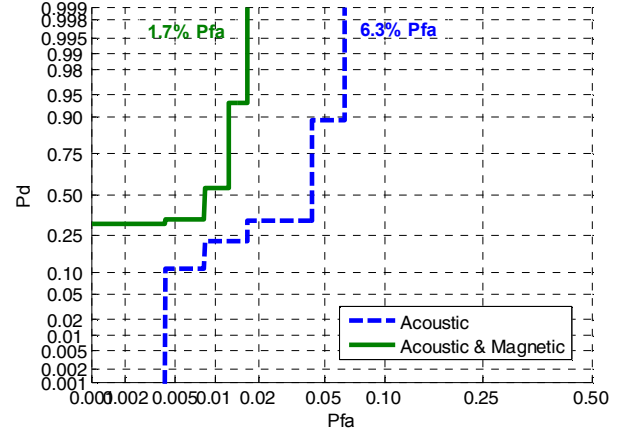


Figure 5. JBC ROC curves for sea-trial data using acoustic features only (dashed blue curve) and both acoustic and magnetic features (solid green curve). The P_{fc} at high P_{cc} is 6.3% and 1.7%, respectively.

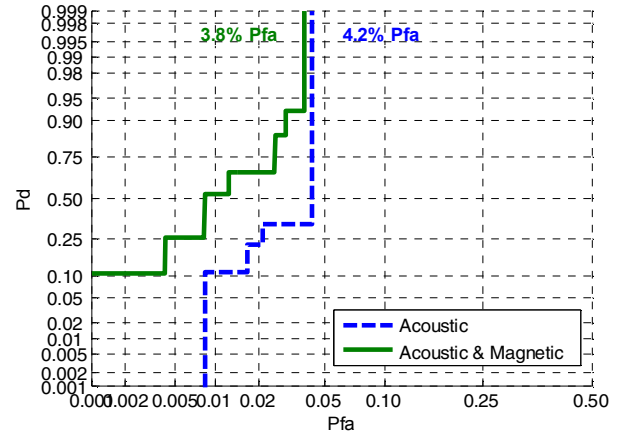


Figure 6. JBC ROC curves for combined sea-trial and synthetic data using acoustic features only (dashed blue curve) and both acoustic and magnetic features (solid green curve). The P_{fc} at high P_{cc} is 4.2% and 3.8%, respectively.

VII. DISCUSSION AND SUMMARY

This paper presents preliminary results of a classification engine that combines target features and classification parameters from a synthetic aperture Buried Object Scanning Sonar (BOSS) and an electromagnetic Real-time Tracking Gradiometer (RTG). Geometric and backscatter intensity features automatically extracted from three-dimensional acoustic imagery were combined with magnetic dipole mo-

ment and associated parameters in a joint-Gaussian Bayesian classifier (JBC), which makes mine-like/non-mine-like decisions for each contact. Nine acoustic and eleven magnetic field data runs were processed to yield acoustic and magnetic features, supplemented by synthetic data. An initially large variety of feature types was down-selected by a training process to a critical subset. With this limited dataset, initial results show probabilities of false classification (P_{fc}) from 1.6% to 6.3% when at high probability of correct classification (P_{cc}). These early results are encouraging and further work is proceeding with dual-sensor synoptic data sets being collected throughout the summer of 2006.

This implementation of the classifier demonstrates sensor fusion at the feature level, where measured characteristics from two sensors are combined into a single feature vector. The utility of fusion at the data level was demonstrated by using BOSS derived locations to constrain RTG solutions. Future work will investigate fusing sensors at the decision-output level and incorporating specific target information into the classifier engine.

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