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Countermine Lidar UAV-based System (CLUBS)

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LONG-TERM GOALS

The long-term goal of this work is to examine the utility of commercial bathymetric lidar technology solely, and in combination with commercial passive imaging spectrometers, for measuring environmental information for military applications in the littoral zone. These findings will indicate how commercial systems might evolve to achieve improved performance for rapid environmental assessment, and for deployment in unmanned aerial vehicles.

OBJECTIVES

1. Develop new classifiers using rule-based, blob-level techniques to combine lidar and hyperspectral data, and compare new results to those achieved using pixel-level fusion algorithms developed in previous phases of the project.

2. Apply a new inversion algorithm to hyperspectral data to produce seafloor reflectace data cubes, and analyze the data cubes to identify minimal spectral bands for seafloor classification.

3. Refine the water column volume visualizer developed in earlier work, so that it may be used for editing and analysis of lidar data.

4. Improve the REA software making it more robust and stable, and improve the user documentation.

5. Investigate use of REA software with data produced by other sensors.

APPROACH

In earlier work, we developed techniques to accomplish seafloor classification from SHOALS lidar data alone, and by fusing SHOALS data with CASI hyperspectral data [1], [2]. These pixel-level fusion algorithms were implemented in the Rapid Environmental Assessment (REA) Processor, and that software was delivered to ONR in March of 2008. In this phase, we develop more sophisticated approaches for fusion and classification by increasing the level of abstraction in both the spatial and information contexts of the measured data. Our approach includes the addition of a mean-shift

algorithm to REA for generation of spatial blobs, and the application of set theoretic techniques to find the intersection and union of blobs identified separately in the lidar and spectral data. We also add to REA the capability to produce blob-level seafloor classifications using decision rules automatically generated with the See5 software. These new capabilities support the analysis of the extended information feature space derived from both the active and passive data, with the goal of finding a subset of optimal features for seafloor classification. Subsequent to our earlier reported results, we developed a more sophisticated constrained inversion algorithm to produce spectral reflectance images of the seafloor [3]. In this phase of CLUBS we use those algorithms to produce improved images from the raw airborne data acquired in the previous phases.

In addition to our efforts to improve the accuracy of seafloor classification, we extend the functionality of the water column volume visualizer by adding the capability to auto-detect the sea surface and seafloor, and develop the necessary hooks into the raw data to allow use of the volume visualizer for data editing.

WORK COMPLETED

Funding for this phase of CLUBS was awarded in February 2010. In the subsequent 7 months we completed the following work:

We developed a blob generation procedure based on a mean-shift algorithm [4], and implemented this blob generator in REA. Given any arbitraty raster spatial image stack defining a feature space, our mean-shift approach searches for similarity in the feature domain, and connectivity in the spatial domain, to segment the spatial image into labeled blobs. This blobbing procedure is an improvement over simple region-growing algorithms tested earlier, and is an important step towards implementing higher-level fusion algorithms to combine the lidar and hyperspectral data.

We developed and implemented into REA a Bhattacharyya Distance (BD) classifier [5], which measures the distance between the data distribution of a blob, and the data distributions of ground truth regions of interest (ROI), and assigns the blob to the nearest ROI distribution in terms of the distance computed within the feature space.

We integrated the automatic rule generation software, See5, into REA and refined REA to parse the output rules from the See5 classifier to generate rule-based classification images.

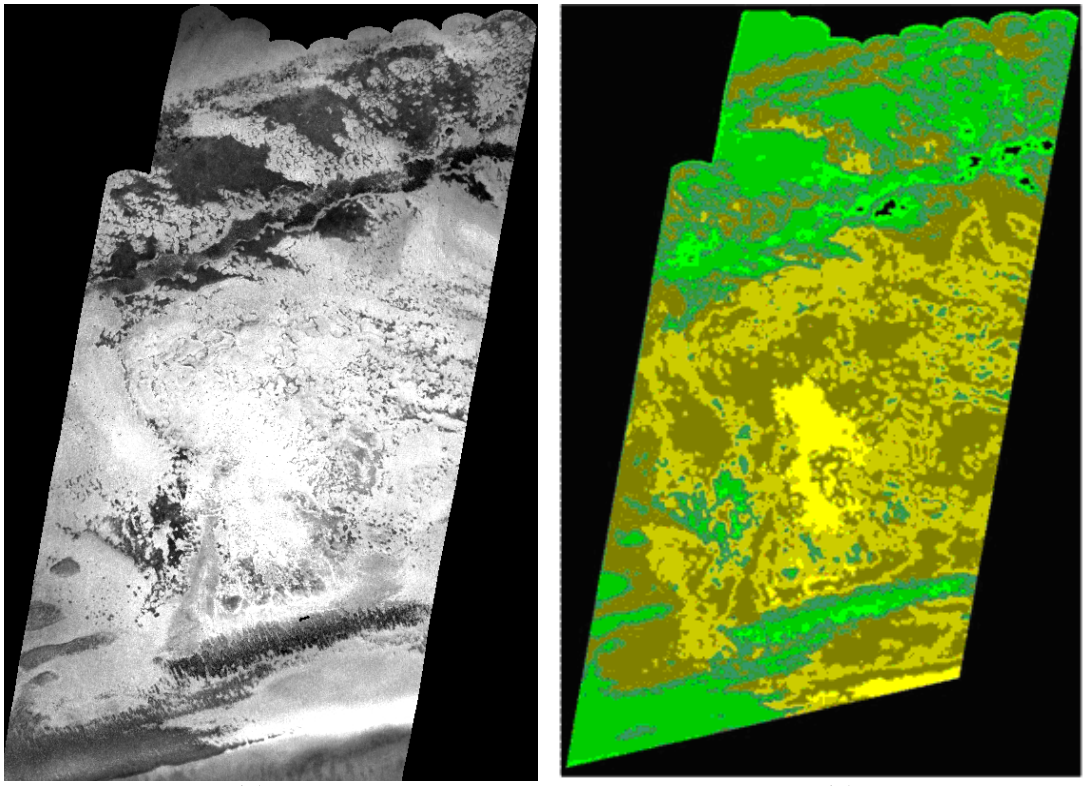
Using a new spectral optimization algorithm computing a constrained inversion of the CASI data, and new algorithms for estimation of SHOALS backscattering, we re-processed the SHOALS and CASI datasets to produce improved seafloor reflectance images from the active and passive data. All new classification work is based on these images.

We implemented algorithms to auto-detect the surface and seafloor in the water column volume visualizer, and implemented the ability to rapidly generate water column visualizations in arbitrarily drawn regions of interest.

RESULTS

We implemented a mean-shift blob generator into REA and are tuning its performance for improved sensitivity and accuracy. We are also using it to understand the information content within derived

feature spaces. For example, in Figure 1 (b), we show the spatial blobs resulting from analysis of the 8 information features generated by gray level co-occurance matrix (GLCM) analysis of the SHOALS seafloor reflectance image of Looe Key, Florida (Figure 1 (a)). The 8 features generated in GLCM analysis are: mean, variance, homogeneity, contrast, dissimilarity, entropy, second moment, and correlation [1]. In blobbing this feature space we used L2-norm as the similarity metric. Here, our blobbing algorithm identified seven distinct clusters within the manifold, and labeled similar blobs with the same color. On inspection, we see that two different sand types are well-separated. But, due to subtle differences between the GLCM textures for sea grass and the linear reef in the top third of the image, those two types are not well-separated in the blob image. We expect this separability to improve with subsequent tuning of the mean shift parameters, and with selection of other information features derived from the lidar measurements (e.g. rugosity and waveform shape parameters).

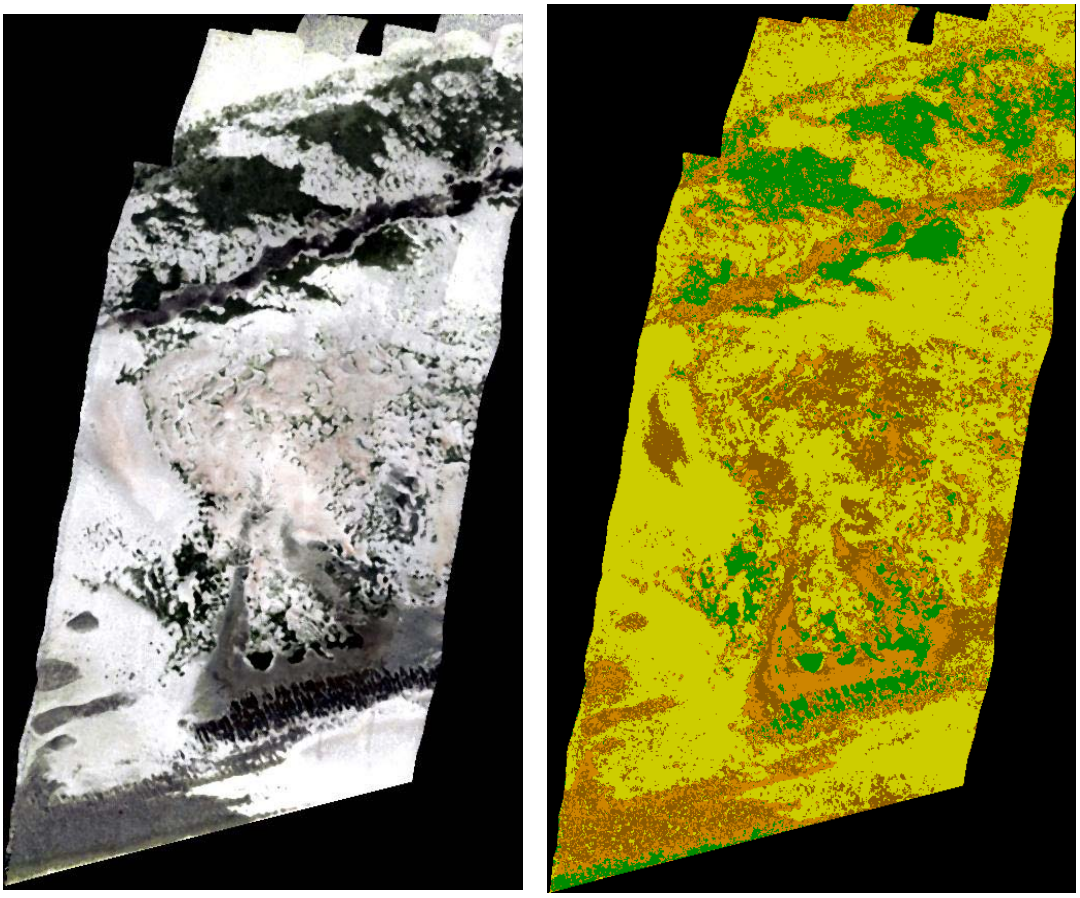


(a) ***(b)***

Figure 1. Grayscale Looe_Key SHOALS seafloor reflectance image (a), Blobbed image using all the eight features of the GLCM analysis (b). Seven different texture classes are found by the mean shift clustering process.

We can identify blobs in the CASI seafloor reflectance datacube using the same mean shift blobbing procedure, but in this case we use spectral angle mapper (SAM) as the similarity metric. In Figure 2, we show results using the first 12 spectral channels of CASI data (wavelengths less than 600nm), where the CASI seafloor reflectance images have been inverted using the Spectral Optimization Algorithm [3]. Here, our mean shift blobbing algorithm has identified 4 modes in the manifold corresponding to 4 bottom types in the spatial data. Upon comparison with Figure 1, we see a good separation between the linear reef and the sea grass. This success arises from the fact that the water is

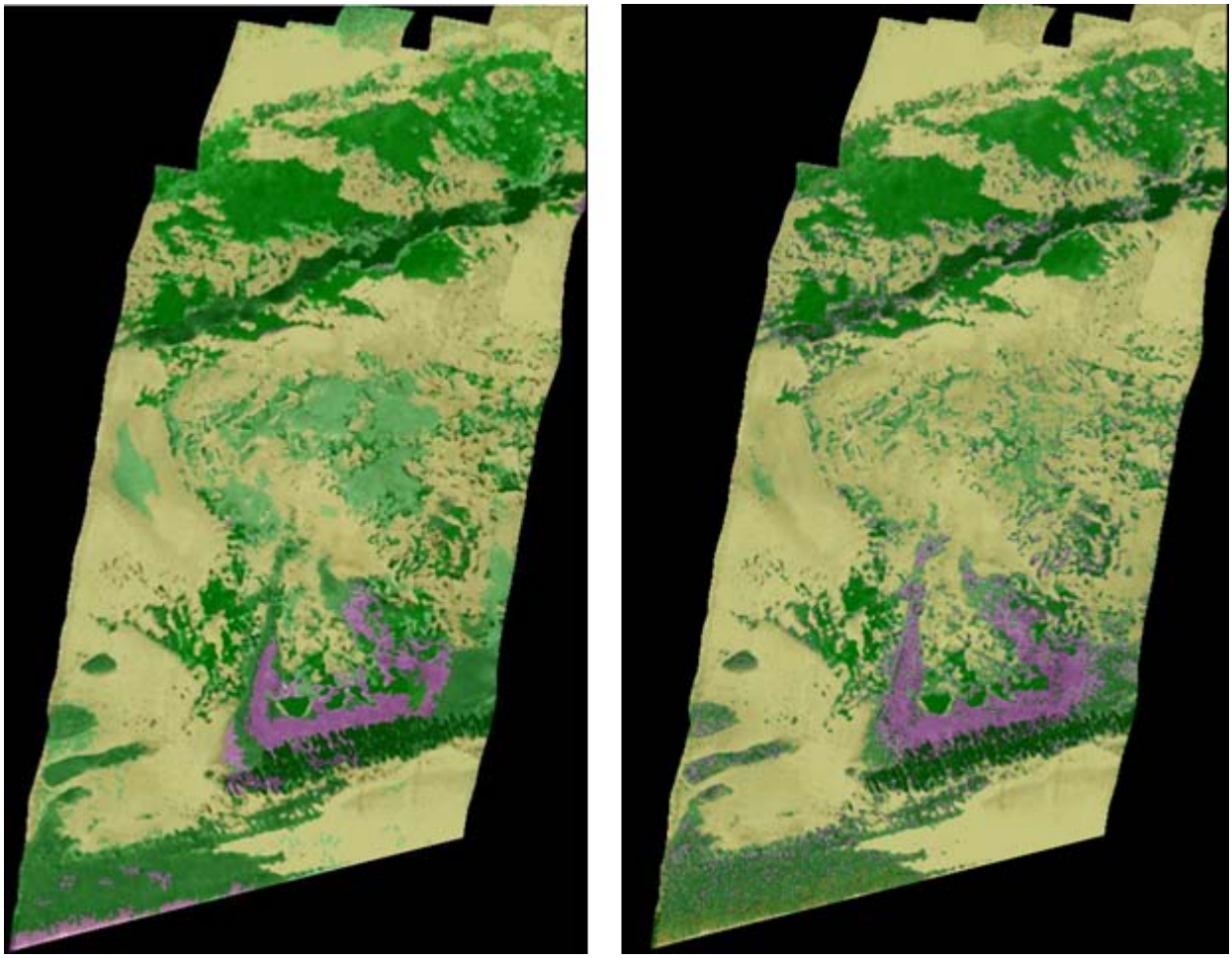
very shallow in this dataset, and at the time of data collection it was very clear. Under these conditions, the spectrometer can be used to achieve accurate seafloor classification.



(a) ***(b)***

Figure 2. RGB composite of (Red:597nm Green:537nm Blue:477nm) Looe_Key CASI bottom image (a), Blob image using the first twelve bands (wavelength < 600nm) as features of the CASI bottom image (b)

To illustrate the difference between pixel-level and blob-level classification with passive seafloor reflectance spectra, we apply a Bhattacharyya Distance (BD) [5] classifier to the blob image shown in Figure 2(b), using 7 training ROI's belonging to four different sea floor bottom types. This procedure creats the blob-level classification map shown in Figure 3(a). In Figure 3(b), we show a pixel-level classification produced by applying a maximum likelyhood classifier (MLC) to the same initial 12 channels of spectral data, using the same training set. The mapped classifications are sand, reef, reef rubble, and sea grass. On inspection, the two classifications look similar. But a formal accuracy assessment reveals that the blob-level classifier is better. The overall accuracy of the blob-level approach is 82%, whereas the accuracy of the pixel level classifier is 75%. (We show the complete accuracy assessments in Table 1 and Table 2).



(a) ***(b)***

Figure 3. Classification image output from a BD classifier applied on a blobbed image using the first twelve bands (wavelength < 600nm) as features of the CASI bottom image (b). Classification image output from a Maximum likelihood classifier(MLC) applied on the first twelve bands of the CASI bottom image (Sea Grass: green, Coral Reef: dark green, Reef Rubble: orchid, and Sand: yellow)

Table 1: Confusion matrix and the overall accuracy table for the classification image shown in Figure 3(a).

Class Name	Reef 1 (Linear)	Reef Rubble	Reef 2 (Deep)	Sand 1	Sea Grass1	Sea Grass2	User Accuracy
Reef 1 (Linear)	1190	99	23	396	12	45	67.4%
Reef Rubble	0	2540	124	0	0	9	95.0%
Reef 2 (Deep)	251	48	2332	103	49	14	83.3%
Sand 1	5	0	0	7453	4	6	99.8%
Sea Grass 1	0	3	0	0	2897	399	87.8%
Sea Grass 2	0	377	0	0	1527	1569	45.2%
Producer Accuracy	82.3%	82.8%	94.0%	88.6%	64.5%	76.8%	81.98%

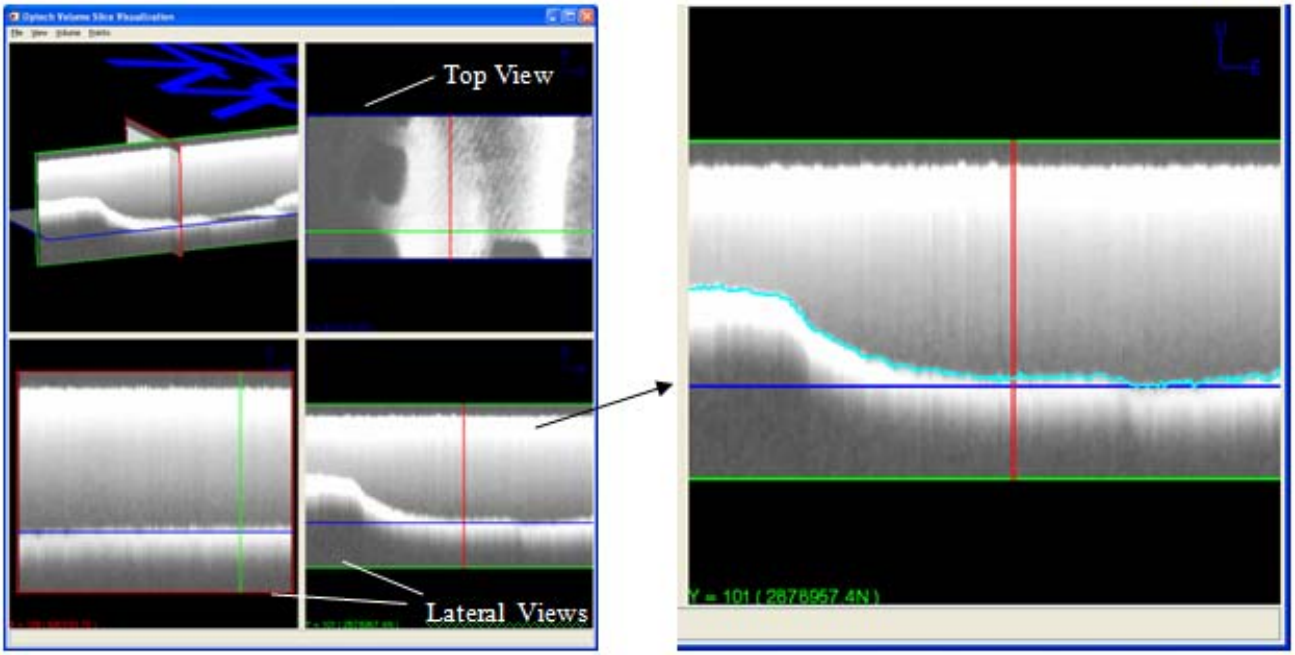
Table 2: Confusion matrix and the overall accuracy table for the classification image shown in Figure 3 (b).

Class Name	Reef 1 (Linear)	Reef Rubble	Reef 2 (Deep)	Sand 1	Sea Grass1	Sea Grass2	User Accuracy
Reef 1 (Linear)	1260	203	724	76	16	17	54.8%
Reef Rubble	128	2739	387	1	33	58	81.86%
Reef 2 (Deep)	50	88	1249	11	11	8	88.1%
Sand 1	0	0	0	3970	0	0	100%
Sea Grass 1	3	35	1	0	3123	871	77.4%
Sea Grass 2	4	2	7	0	1283	1073	45.29%
Producer Accuracy	87.2%	89.31%	53.7%	87.9%	69.9%	52.9%	75.0%

We believe it is possible to improve the results of fusion-based classification by intersecting spatial blobs from the active and passive data, and using decision-level strategies to classify the intersected blobs. To support this work, we integrated the See5 decision rule generator into REA. It is our intent to use these tools to generate a general set of decision rules applicable in a wide range of geomorphologies and environments. To do this, we must process a large number of datasets from around the globe. Unfortunately, our anticipated access to the Naval Oceanographic Office (NAVO) data library was not granted because of data security concerns expressed in that organization. We are in the process of obtaining unclassified U.S. coastal data from the U.S. Army to support this work task.

In earlier phases of CLUBS, we developed a novel tool to visualize lidar data in terms of the returned backscatter. At present, this tool exists as a only visualization tool – not as a metric tool. In this phase of CLUBS, we propose it to expand its utility for data editing.

In this phase of work we developed the ability to draw Regions of Interest (ROIs) under which the water column is displayed. This is a significant improvement over earlier versions in that the gridding to voxelize the water column occurs only after an ROI is drawn by the user. We are also currently exploring acceleration strategies including moving the required computations onto the Graphical Processing Unit (GPU).



(a) *(b)*

Figure 4. Volume Visualizer showing the data cube of size ~0.6 x0.2 km^2. The second, third and fourth quadrants show the top and lateral slices of the data cube (a) and Detected sea floor overlaid as a vector (b).

We have also added built-in routines to detect the water surface and seafloor topography by the implementation of edge detectors in the three orthogonal planes defining the lidar backscatter data cube. To date, we have used Sobel and Laplacian of Gaussian (LOG) edge detectors with good

success. The user can overlay these edges as vectors in each of the three multi-planar displays. This functionality is available through the pull down menu of the Volume Visualizer. We show preliminary output of this functionality developed in the reporting period in Figure 4 (b).

IMPACT/APPLICATIONS

The blob-level classification procedure developed in CLUBS shows a promissing way of moving pixel-level fusion to blob-level fusion for lidar and hyperspectral data. We have learned that the kernel density estimation and mean shift algorithm generate impressively well-defined blobs with proper input parameters. To determine the identity of the blobbed objects, we also have to develop classifiers for blobs or adopt decision making algorithms, like the rule-based approach.

The Bhattacharyya Distance (BD) classifier measures the distance between the data distribution corresponding to one blob, and distributions for ground truth ROIs. Our results indicate that higher accuracy is achieved following this approach as compared to pixel-level classifiers. But the BD based classifer still requires a training sets. We are developing methods to use automatic rule generation software to avoid the requirement for site specific ground truth.

The faster speed of the volume visualizer makes it possible to use this 3-dimensional visualization tool to understand backscattering changes in water column from water surface to the seafloor. It can now readily be used to locate small objects in the water column, and objects or layers floating below the water surface. This enables developing automatic 3 directional scanning capability to detect outliers and determine depths from surface and seafloor edge boundaries.

All algorithms and software have been integrated into the Rapid Environmental Assessment (REA) Processor.

TRANSITIONS

We will commercialize the REA processor and promulgate its use for a wide range of benthic mapping applications. For the past year, the Joint Airborne Lidar Bathymetric Technical Center of Expertise (JALBTCX) has served as a beta test site for this software.

The basic funtionality of the algorithms will be adopted into the Coastal Zone Mapping and Imaging Lidar (CZMIL) to be built by Optech at its offices in Kiln, Mississippi.

RELATED PROJECTS

Coastal Zone Mapping and Imaging Lidar (CZMIL). CZMIL is a strategic partnership between Optech International and the Department of Marine Science at the University of Southern Mississippi leading to the design and construction of a next generation bathymetric lidar to improve performance in shallow water, and achieve water column and seafloor characterizations. The CZMIL project will also establish an industry/government/academic center of expertise for bathymetric lidar.

REFERENCES

[1] Tuell, G., “Countermine Lidar UAV-based Sytem (CLUBS)”, Annual Report for Project N00014-05-C-0417, FY06.

[2] Tuell, G., “Countermine Lidar UAV-based Sytem (CLUBS)-Year 2”, Annual Report for Project N00014-05-C-0417, FY07.

[3] Kim, M., Park, J.Y., Tuell, G. “ A constrained optimization technique for estimating environmental parameters from CZMIL hyperspectral and lidar data”, Proceedings Vol. 7695, Algorithms and Technologies for Multispectral, Hyperspectral, and Ultraspectral Imagery XVI, Sylvia S. Shen; Paul E. Lewis, Editors, 76950U.

[4] F. Li and R. Klette, “Adaptive Mean Shift Based Clustering,” in proc. Int. conf. on advances in neuron-information processing, Nov. 2008.

[5] Kailath, T., “The Divergence and Bhattacharyya Distance Measures in Signal Selection,” IEEE Trans. on Comm. Tech., pp. 52-60, 1967.