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Topics: Ground truth, Standard test image and Test data

Unresolved Target Detection Blind Test Project Overview

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ABSTRACT

The development and testing of algorithms for unresolved target detection in hyperspectral imagery requires the availability of empirical imagery with adequate ground truth. However, target deployment and collection of imagery can be expensive, and the resulting data often have limited distribution due to concerns of a security or propriety nature. When data are made available, it is usually with full ground truth leading to the possibility of analysts "tuning" their algorithm and reporting optimistic results. There exists an ongoing need for widely available, well ground truthed, and independent data for the community. This paper provides an overview and introduction to such a standard blind test data set. Airborne hyperspectral imagery is provided together with spectral reflectance signatures of several fabric panels and vehicles in the scene. A self-test image is accompanied by pixel locations in the image for the targets of interest for algorithm development. A blind test image has additional targets in different locations and is provided without pixel truth for independent performance assessment. Since publicizing the data set in 2008, over 150 researchers from around the world have downloaded the data for testing. Further details on the data, the project, and the results of participants are presented.

Keywords: Hyperspectral target detection, blind test

1. INTRODUCTION

The development and testing of algorithms for unresolved target detection in hyperspectral imagery requires the availability of empirical imagery with adequate ground truth [1]. However, target deployment and collection of imagery can be expensive, and the resulting data often have limited distribution due to concerns of a security or propriety nature. When data are made available, it is usually with full ground truth leading to the possibility of analysts "tuning" their algorithm and reporting optimistic results. There exists an ongoing need for widely available, well ground truthed, independent, and standardized data for the community.

In the mid-1990's, several "radiance" experiments were conducted in the United States with the HYDICE airborne hyperspectral imager. Desert Radiance II [2] and Forest Radiance I [3] were designed for target detection studies and included excellent ground truth collection. These data were distributed to a number of researchers and formed the basis for many research efforts and resulting publications which significantly advanced the state-of-the-art in hyperspectral target detection. However, these data are not widely available, and new researchers are prevented from testing new and improved algorithms.

In the context of hyperspectral land cover classification, there exists a widely used data set which is freely available. The Indian Pines 1992 AVIRIS data set distributed with Purdue's MultiSpec software developed by Landgrebe and Biehl [4,5], has been used by numerous researchers. This data set comes with pixel by pixel ground truth for sixteen ground cover classes. Its complete ground truth and free distribution have made it very popular as a test data set for high dimensional classification algorithm development. The popularity has continued to grow as it has become a de facto standard data set since subsequent researchers use it to compare results from their new algorithm to the published results of previous researchers.

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However, since the Indian Pines data set comes with the ground truth, and the classification accuracy is scored by the researchers, the possibility exists that the researchers will "tune" their algorithms to provide the best possible performance on the given data. An alternative is to distribute data without the truth and then have an independent mechanism to compute accuracies given an algorithm's result. This was the model used in the recent Data Fusion Contest organized by the Data Fusion Technical Committee of the IEEE Geoscience and Remote Sensing Society [6]. This contest kept the land cover map secret and included an automated classification accuracy computation upon uploading of the analysts class map.

Providing data for such a blind test with automatic scoring for hyperspectral unresolved target detection was the motivation for our project initiated in 2007. Using data collected in 2006, we developed a web site for distribution and automated detection scoring which has been available to the community since 2008 [7]. The following sections provide updated details on the data set, the scoring mechanism, and a summary of the current community participation and results.

2. DATA SET DESCRIPTION

2.1 Data collection overview

The target deployments, airborne and ground truth data collection were performed in the context of a research project funded by the U.S. Air Force Research Laboratory and in cooperation with HyPerspectives, Inc. The experiment was conducted in the small town of Cooke City, Montana, USA. Multiple fabric targets were deployed for tests of unresolved target detection, and several vehicles were used for repeat pass tracking of their movement. Airborne hyperspectral imagery was collected by the HyMap sensor [8] with multiple passes occurring. While the experiment was planned for July 3, 2006, equipment problems prevented the airborne data collection and thus the targets were re-deployed and imaged on the Independence holiday, July 4, 2006.

HyMap was flown at approximately 1.4 km above the terrain yielding 3 meter ground resolution. Figure 1 shows the self test image. The blind test image looks nearly the same.

Figure 1. RGB of self test image showing Cooke City and surrounding terrain.

2.2 Targets

Several fabric panels of various sizes were deployed as targets. Table 1 shows the fabric targets provided with truth for the self test image while Table 2 shows the targets for the blind test image. The first two in the self test, fabrics F1 and F2, were 3 m x 3 m, or nearly a full pixel. All other fabric targets were smaller and occupied less than a pixel.

Table 3 shows the three vehicle targets for which truth pixel locations are provided for the self test image. They occupy at most a few pixels, but are visually difficult to detect. The vehicles are in different locations for the blind test image.

Table 1. Self test fabric targets.

Fabric Code	Size(s)	Description
F1	3 m x 3 m	Red cotton
F2	3 m x 3 m	Yellow nylon
F3	1 m x 1 m, 2 m x 2 m	Blue cotton
F4	1 m x 1 m, 2 m x 2 m	Red nylon

Table 2. Blind test fabric targets.

Fabric Code	Sizes	Description
F5	1 m x 1 m, 2 m x 2 m	Maroon nylon
F6	1 m x 1 m, 2 m x 2 m	Grey nylon
F7	1 m x 1 m, 2 m x 2 m	Green cotton

Table 3.Vehicle targets present in both the self test and blind test images (but different locations).

Vehicle Code	Description
V1	Green Chevy Blazer
V2	White Toyota T100
V3	Red Subaru GL

A picture is provided for each target with the data distribution package. Their spectral reflectances are provided in both ENVI spectral library format as well as plain text. For the self test targets, ENVI-compatible Region of Interest (ROI) files are provided to specify their locations in the image.

2.3 Images

The self test and blind test images are both 800 columns by 280 lines by 126 bands, spanning 0.45 to 2.5 μm. The self test image was acquired at 9:42 am Mountain Daylight Time (MDT), while the blind test was acquired earlier at 9:20 am MDT. Both are distributed as calibrated spectral radiance as well as after atmospheric compensation as reflectance. All images are stored as two-byte integers. The spectral radiance versions have units of $\mu W/(cm^2\text{-sr-nm})$, but are scaled by 1000 for bands 1- 62, and 4000 for bands 63 – 126. The reflectance images are in units of reflectance factor scaled by 10,000. All images are provided with an ENVI-compatible header.

3. WEBSITE AND AUTOMATIC SCORING

3.1 Registration and data download

Users are asked to register before downloading the data to help keep track of usage and to be able to provide notification of any changes to the website. The self test and blind test data are provided in separate compressed files in both .zip and .bz2 formats. The website contains short descriptions of all targets, images, and ground truth files [9].

3.2 Automatic scoring

For each blind test target, the user is asked to provide a scalar test statistic image with the value at each pixel proportional to the likelihood that the target of interest is present (a greater value indicates more likely). This image is uploaded together with an ENVI-compatible header file provided by the user. The user can also provide text strings describing the algorithm and version information. The automatic scoring algorithm then takes the value at the known pixel location of the target and counts the number of pixels in the entire image with that value and higher. Thus, a perfect score is 1, indicating the target of interest was found with no additional false alarms. This score is provided immediately to the user.

4. COMMUNITY ACTIVITY

4.1 Participation

To date, 164 distinct users have registered for access to the web site. Of these, 126 have downloaded the data set at least once, but only 10 have uploaded results for scoring on the blind test image. However, those who have uploaded results have done it multiple times testing many different algorithms and versions.

The users are asked to indicate their organization, and from these self reported identifications, we see participation has been worldwide with researchers from North America, Europe, Asia, and Australia. While most participants report being at a university, a significant number also are located at research and industrial organizations.

4.2 Results

A key feature of the website is a listing of the current 10 best results for each of the targets in the blind test data set. Participants are invited to identify their algorithm by a name and a version, which is then listed in the table along with the score and rank. The table is updated after each submission of results.

The following tables show the Top 10 as of March 6, 2010. Tables 4 - 9 show results for the fabric targets while Tables 10 - 12 include results for the vehicles. The algorithm name and versions are provided by the users. The smaller instances of the fabrics are generally more difficult to detect and have higher scores (corresponding to more false alarms). Also, the vehilces are more difficult to detect due to a lack of spectral features present in their reflectance.

Table 4. Target: F5 1x1m Maroon Nylon.

Score	Algorithm Name	Algorithm Version	Rank
5	Global RX-Masked ACE	.1 (top score mapped to single superpixel)	1 of 108
6	Local ACE	.1 (top score mapped to single superpixel)	2 of 108
6	Stochastic ACE	.1 (top score mapped to single superpixel)	2 of 108
7	ENVI HG + usharp + MF + manual	7pt	4 of 108
9	Local Background Suppressed ACE	.1 (top score mapped to single superpixel)	5 of 108
11	TAD-signedACE	0.1	6 of 108
11	Illumination-mod TAD-sACE	0.1	6 of 108
11	Isaac Gerg	ACE,apriori target	6 of 108
11	Global ACE	.1 (top score mapped to single superpixel)	6 of 108
14	Isaac Gerg	HUD,apriori	10 of 108

Table 5. Target: F5 2x2m Maroon Nylon

Score	Algorithm Name	Algorithm Version	Rank
1	hK+	gTs	1 of 108
1	TAD-signedACE	0.1	1 of 108
1	ace	((x-u)G(t-u))^2/((t-u)G(t-u)*(x-u)G(x-u))	1 of 108
1	signedACE	((x-u)G(t-u))*|(x-u)G(t-u)|/((t-u)G(t-u)*(x-u)G(x-u))	1 of 108
1	Illumination-mod TAD-sACE	0.1	1 of 108
1	ENVI hourglass + threshold 8 deg	1.0	1 of 108
1	ENVI hourglass +usharp + manual selection	1 pt	1 of 108
1	ENVI hourglass +usharp + manual selection	1pt lower MF score	1 of 108
1	ACE plus FM on Radiance	k=1	1 of 108
1	ACE plus AC on Reflectance	-	1 of 108

Table 6. Target: F6 1m x 1m Gray Nylon

Score	Algorithm Name	Algorithm Version	Rank
3	Local BS ACE	.1 (top score mapped to single superpixel)	1 of 70
5	SB-GLRT plus AC on Reflectance	k_bck=35	2 of 70
5	Isaac Gerg	ACE - bands 1:100 - PCT 95	2 of 70
5	Global ACE	.1 (top score mapped to single superpixel)	2 of 70
5	Local ACE	.1 (top score mapped to single superpixel)	2 of 70
6	hK+	lfs	6 of 70
6	TAD-signedACE	0.1	6 of 70
6	signedACE	((x-u)G(t-u))*|(x-u)G(t-u)|/((t-u)G(t-u)*(x-u)G(x-u))	6 of 70
6	Band Filtered Ace	0.1	6 of 70
7	ACE	((x-u)G(t-u))^2/((t-u)G(t-u)*(x-u)G(x-u))	10 of 70

Table 7. Target: F6 2m x 2m Gray Nylon

Score	Algorithm Name	Algorithm Version	Rank
1	hK+	lfs	1 of 70
1	TAD-signedACE	0.1	1 of 70
1	ACE	((x-u)G(t-u))^2/((t-u)G(t-u)*(x-u)G(x-u))	1 of 70
1	signedACE	((x-u)G(t-u))*|(x-u)G(t-u)|/((t-u)G(t-u)*(x-u)G(x-u))	1 of 70
1	Illumination-mod TAD-sACE	0.1	1 of 70
1	ACE	AC+refl	1 of 70
1	ACE plus FM on Radiance	k=1	1 of 70
1	ACE plus AC on Reflectance	-	1 of 70
1	SB-GLRT plus AC on Reflectance	k_bck=35	1 of 70
1	SB-GLRT plus FM on Radiance	k=1, k_bck=25	1 of 70

Table 8. Target: F7 1m x 1m Green Cotton

Score	Algorithm Name	Algorithm Version	Rank
7	Local ACE	.1 (top score mapped to single superpixel)	1 of 58
9	ACE refl	lo	2 of 58
13	Illumination-mod TAD-sACE	0.1	3 of 58
35	Stochastic ACE	.1 (top score mapped to single superpixel)	4 of 58
45	hK+	gTs	5 of 58
46	TAD-signedACE	0.1	6 of 58
54	Global RX-Masked ACE	.1 (top score mapped to single superpixel)	7 of 58
164	Band Filtered Ace	0.1	8 of 58
447	ACE plus AC on Reflectance	-	9 of 58
625	Isaac Gerg	ACE, bands 1:80	10 of 58

Table 9. Target: F7 2m x 2m Green Cotton

Score	Algorithm Name	Algorithm Version	Rank
1	signedACE	((x-u)G(t-u))*|(x-u)G(t-u)|/((t-u)G(t-u)*(x-u)G(x-u))	1 of 58
1	Global ACE	.1 (top score mapped to single superpixel)	1 of 58
1	Local BS ACE	.1 (top score mapped to single superpixel)	1 of 58
2	ACE	((x-u)G(t-u))^2/((t-u)G(t-u)*(x-u)G(x-u))	4 of 58
2	AB-hybrid	max of ACE-ACENM-IMF-PIMF	4 of 58
2	Isaac Gerg	ACE	4 of 58
2	Global RX-Masked ACE	.1 (top score mapped to single superpixel)	4 of 58
2	Local ACE	.1 (top score mapped to single superpixel)	4 of 58
10	Stochastic ACE	.1 (top score mapped to single superpixel)	9 of 58
13	TAD-signedACE	0.1	10 of 58

Table 10. Target: V1 1993 Chevy Blazer

Score	Algorithm Name	Algorithm Version	Rank
15	ENVI HG + usharp + MF + manual	15pt	1 of 36
42	Illumination-mod TAD-ACE	0.1	2 of 36
42	TAD-ACE	0.1	2 of 36
56	Isaac Gerg	ACE, 2	4 of 36
58	Illumination-mod TAD-sACE	0.1	5 of 36
188	Band Filtered Ace	0.1	6 of 36
306	clda	0.01	7 of 36
312	Matched Filter (bands up to 94)	(x-u)G(t-u)/((t-u)G(t-u))	8 of 36
499	clda+pca	0.02	9 of 36
660	CEM	0.01	10 of 36

Table 11. Target: V2 1997 Toyota T100

Score	Algorithm Name	Algorithm Version	Rank
196	Illumination-mod TAD-sACE	0.1	1 of 41
246	TAD-signedACE	0.1	2 of 41
278	Isaac Gerg	ACE, 2	3 of 41
341	TAD-ACE (In Scene Spectra From Self Test)	1.0	4 of 41
417	ace	0.01	5 of 41
580	Illumination-mod TAD-sACE (bed spectra)	0.1	6 of 41
582	Band Filtered Ace	0.1	7 of 41
618	CEM	0.01	8 of 41
813	clda	0.01	9 of 41
820	MF/SAM	ENVI using band math	10 of 41

Table 12. Target: V3 1995 Subaru GL Wagon

Score	Algorithm Name	Algorithm Version	Rank
112	Isaac Gerg	SAM,2,90	1 of 55
112	Isaac Gerg	SAM,2,80	1 of 55
112	Isaac Gerg	SAM,2,70	1 of 55
617	Illumination-mod TAD-sACE	0.1	4 of 55
723	cem+pca	0.01	5 of 55
856	cem+pca	0.02	6 of 55
1110	Isaac Gerg	ICA-EEA,2	7 of 55
1141	TAD-signedACE	0.1	8 of 55
1555	kglrt+pca	0.02	9 of 55
1707	amf+pca	0.01	10 of 55

5. SUMMARY AND CONCLUSIONS

Hyperspectral imagery with accompanying ground truth for targets has been made available to the hyperspectral target detection community for algorithm development and testing. For the self test image, the precise pixel locations of various targets are provided along with their reflectance spectra for users to develop and test algorithms on their own. Additionally, a blind test image is provided with target spectra, but without pixel locations for the targets. The user may then upload their detection results for scoring by an automated program. The top ten scores for each target are posted in tables on the website to allow users to compare their results to others and to encourage algorithm development.

The blind test data set has proved to be popular with well over one hundred participants registering and downloading the data. Many have tested a variety of algorithms to see how they compare on these data. The blind test aspect and the reporting of the top scores have helped prevent the tuning of algorithms for comparisons and have promoted a sense of competition among the participants. It is suggested additional data sets be made available in a similar manner by other research groups for further testing by the community.

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